THE CONTRIBUTION OF ANALYTIC INFORMATION PROCESSING TO DIAGNOSTIC PERFORMANCE IN MEDICINE

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Analytische verwerking van informatie en diagnostische prestatie in de geneeskunde

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To Caren and wee Cate – milk and sugar in the tea of life

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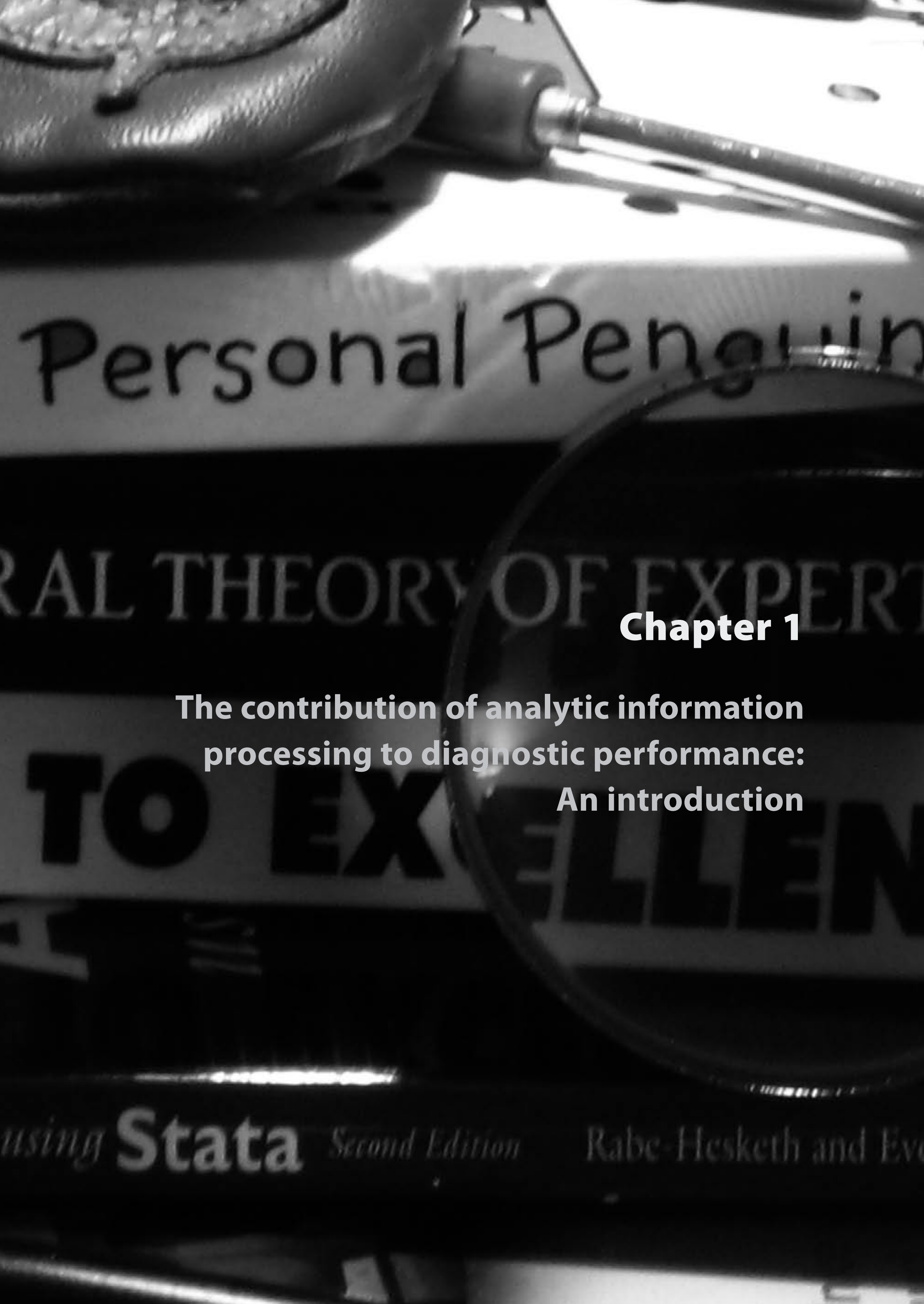

Chapter 1

The contribution of analytic information processing to diagnostic performance: An introduction

Finding the recipe for medical expertise

Compared to non-experts, experts in medicine consistently demonstrate superior diagnostic performance in their area of expertise. Those of us involved in studying medical expertise are driven by the same question, "what is the recipe for superior performance?" We are wannabe chefs who have tasted a wonderful meal and rush home to create this ourselves, digging in books to find the recipe. On discovering there is no recipe, we proceed to identify the ingredients, confident that one day we will recreate this meal for our colleagues, our students and ourselves. We soon discover it is a complicated recipe. There are two key ingredients, biomedical and clinical knowledge, both of which can be cooked in two ways – by automatic or analytic processing. To add to the confusion we discover that the ingredients are not independent – biomedical influences the flavour of clinical and vice versa. Similarly, cooking styles are interdependent – automatic processing seems to influence analytic processing and vice versa. So we speak to the expert chefs themselves, but they tell us they cook to taste and no longer follow a recipe. For them it is intuitive; as much art as science. To add to our despair the experts tell us that it took them at least ten years of practice to learn how to cook this meal correctly. But still we don't give up the quest because recreating medical expertise is important to us.

One of our primary goals as medical educators is to pass on to others the information that we have discovered. A process as difficult to understand as medical expertise is even more difficult to teach. Faced with the interdependent nature of information and processing types, and the length of time needed to acquire true expertise, we are forced to adopt a reductionist approach to the study and teaching of expertise. So we all study and teach different parts of the recipe, but never the complete recipe. Rather than describing the recipe of medical expertise in general, therefore, this thesis is a collection of studies on a specific aspect of the recipe, analytic information processing, and its contribution of to diagnostic performance. But before describing these studies I would like to review the current paradigm on information processing and the assumptions that underlie this.

Assumptions of information processing

Our current paradigm of information processing is based upon a few, key assumptions: when processing information of a case diagnosticians create mental representations of the problem[1]; mental representations can be probed using recall protocols[2]; and mental representations are used to retrieve stored knowledge.[1] These assumptions are not unique to medicine, having been described initially in non-medical domains, such as chess and computer programming.[3;4]

It was previously assumed than in medicine, as in non-medical domains, experts would have more detailed mental representations and apply more knowledge when diagnosing.[3-5] It was also assumed that knowledge application could be assessed by asking diagnosticians to think aloud while diagnosing and to provide a pathophysiological justification for their diagnosis.[2] But here the finding from medical and non-medical domains diverge.

Mental representations of medical experts are less elaborate than those of intermediates.[6;7] There are also qualitative differences in the mental representations: intermediates typically demonstrating an elaborate network of biomedical (or pathophysiological) information and experts an 'illness script' replete with clinical information – such as predisposing factors, symptoms and sign – but relatively deplete of biomedical information.[1;7] Schmidt and colleagues explained the mental representation paradox – the 'intermediate effect' – by demonstrating that experts integrate or 'encapsulate' lower level, biomedical concepts into a smaller number of higher level, clinical concepts.[8;9]

Assessing knowledge application using think aloud assumes information processing is analytical and diagnoses are justified by pathophysiological explanations. But processing is often non-analytical and diagnoses justified by superficial similarity between present and previously encountered cases rather than pathophysiological explanations.[10] The unconscious, or *automatic*, nature of non-analytic processing means that this must be studied indirectly, such as by observing the effects of manipulating contextual information or previous experience on diagnosis.[10;11] Diagnosing frequently involves automatic processing alone, particularly when experts solve routine problems.[12;13]

Distinct from non-medical domains, therefore, are these assumptions about information processing in medicine: different types of knowledge exist – biomedical and clinical; with increasing experience (or expertise) clinical knowledge predominates and biomedical knowledge becomes encapsulated within clinical knowledge; information processing may be analytic or automatic; think aloud protocols assesses the analytic component of information processing; and experts are more likely to diagnose using automatic processing alone.

Information and processing

There are two components to information processing; *information* and *processing*. There are two types of information that may be processed: clinical and biomedical. Clinical information includes the presenting symptoms and signs, along with contextual (or predisposing) information, such as clinical setting, age, gender, past history and disease-specific risk factors. Biomedical information includes information on anatomy, physiology and pathophysiology. There are also two types of processing: automatic and analytic. Automatic processing, synonymous with pattern recognition, is an effortless, unconscious process, driven by perception, connecting the information of the present case with a previously encountered case. The diagnostic justification here is similarity of information *between* cases. Analytic processing, by contrast, is an effortful, conscious process whereby information of the case is interpreted, analyzed and synthesized. The diagnostic justification here is based upon the information contained *within* the case.

Although biomedical information processing is typically considered to be analytical, this need not be the case. Similarly, clinical information processing may be automatic or analytic or both. This distinction is important and the terms biomedical information and analytic processing, or clinical information and automatic processing, are not interchangeable; *information* is a noun and *to process* is a verb. Chapters 2 through 6 of this thesis involve the study of analytic processing. Chapters 2 and 3 study analytic processing of biomedical information, Chapters 4 and 5 study analytic processing of both clinical and biomedical information, while Chapter 6 studies analytic processing of clinical information alone.

The Current Paradigm Of Information Processing

Making a diagnosis typically begins by generating an initial diagnostic hypothesis from automatic processing of information on a presenting symptom, sign or abnormal test result, along with contextual information.[14-16] If this hypothesis is accepted then information processing stops. Alternatively, automatic processing may be supplemented by analytical processing, involving conscious application of stored clinical and/or biomedical knowledge.[17]

Information processing varies between domains – automatic processing predominating in visual domains and analytic processing being used more frequently when interpretation of laboratory data are involved.[18-20] Processing also appears to vary with clinical experience (or expertise), although opinions differ on whether increasing experience leads to more or less analytic processing.[2;21-24]

The contribution of analytic information processing to diagnostic performance

In this section I will review the details of previous studies that have considered the contribution of analytic processing of clinical and biomedical information to diagnostic performance. Patel *et al.* studied medical students diagnosing a case of acute bacterial endocarditis.[21] Students first read and recalled relevant biomedical texts before reading and recalling text describing the patient's problems, providing a diagnosis and explaining this diagnosis on the basis of the underlying pathophysiology. The authors found that students applied biomedical knowledge inconsistently or incorrectly when explaining their diagnosis, from which they inferred that clinical and biomedical knowledge exist as distinct entities where processing of clinical information is used to make a diagnosis and analytic processing of biomedical information is used to provide a pathophysiological explanation. In this case the contribution of analytic processing of biomedical information to diagnostic performance could be described as *redundant*.

Gilhooly *et al.* studied registrars, house officers and medical students diagnosing and explaining electrocardiograms.[22] They found that increasing expertise was associated with more detailed recall and using more clinical and biomedical information when both *diagnosing* and *explaining*. Lesgold *et al.* studied residents and expert radiologists diagnosing chest X-rays and found that correct interpretation was associated with applying anatomical and pathophysiological knowledge, and that experts applied more of this type of knowledge than resident.[23] The conclusion from these studies was that analytic processing of biomedical information was required for diagnostic success, in which case analytic processing could be described as *critical* to diagnostic performance.

Kulatunga-Moruzi *et al.* used a comprehensive list of clinical features – both for and against the correct diagnosis – to facilitate analytic information processing by dermatologists, family medicine specialists and family medicine residents when diagnosing dermatology photographs.[25] They found that diagnostic performance of experienced physicians was reduced when using a comprehensive features list, in which case the contribution of analytic processing could be described as *detrimental*. In a subsequent experiment, however, they found that using fewer pieces of data – all supporting the correct diagnosis – improved performance of experienced physicians, suggesting that the effect of analytic processing may depend upon both the quantity and quality of information processed.[25]

Boshuizen and colleagues studied medical students and family physicians diagnosing a case of acute pancreatitis.[7] Family physicians and students with clinical experience used fewer biomedical propositions when *diagnosing* the case but more when *explaining* the diagnosis – suggesting that with clinical experience biomedical knowledge is encapsulated within clinical knowledge and applied tacitly during information processing. Several recent studies have supported this finding.[26;27] Verkoeijen *et al.* studied medical students and internists diagnosing electrolyte problems with and without a clinical context.[28] Internists used more analytic information processing when clinical context was absent, demonstrating that, where needed, experienced physicians can unfold encapsulated knowledge and apply this analytically when diagnosing. In this case the contribution of analytic processing of biomedical information could be described as *optional*.

While some of the differences in the contribution of analytic information processing to diagnostic performance observed in these studies are likely due to true variance related to differences in expertise and domain of study, error variance, caused by bias related to study design and technique used to study information processing, may also contribute to the differing conclusions.

Sources of bias when studying information processing

In this section I will discuss strengths and limitations of the various approaches used to study information processing. There is no gold standard technique and each variation in study design and technique carries strengths and limitations, including potential sources of bias:

Observational versus interventional study design

A strength of observational studies is their attempt to observe reality by allowing subjects to make a diagnosis in the experimental setting as they would in real-life.[2;29] However, as subjects are not blinded, simply being studied likely influences information processing – the Hawthorne effect. Depending upon the intrusiveness of the technique used to study information processing, observational studies also introduce a varying degree of performance and determination bias, as is discussed below. A weakness of observational studies is that they show only associations between independent and dependent variables, such as the type of information processing and diagnostic performance. Such results generate rather than test hypotheses and studies that manipulate independent variables – interventional studies – are required to test the hypotheses generated.[10;25] By manipulating a naturally occurring process such as information processing, however, interventional studies necessarily introduce performance bias to a greater or lesser extent.[30]

Minimally intrusive versus intrusive techniques for studying information processing

To reduce performance bias due to the experimental setting minimally intrusive techniques, such as *observation of task performance*, have been used to study information processing.[31] Such techniques are, however, prone to determination bias if the observer has to infer a mental process, or recall bias if the subject has to recall a mental process based upon videotape review. At the other extreme, intrusive techniques, such as *interruption analysis*, are designed to reduce determination bias by stopping the subject and asking for an explanation each time the observer is unclear as to what is happening.[31] But these techniques are prone to performance bias as it may be difficult to restart the same process when it has been interrupted. *Protocol analysis*, which involves subjects being recorded as they 'think aloud' and researchers drawing inferences from transcripts, lies between these extremes.[2]

Contextualized versus uncontextualized data

Automatic information processing is used to process information on a presenting symptom, sign or abnormal test result along with contextual information, such as clinical setting, age, gender, past history and disease-specific risk factors.[16] Providing data without contextual information biases performance towards analytic information processing.[20;28]

Observation versus explanation of information processing

Early studies using protocol analysis to study information processing typically required subjects to provide a pathophysiological explanation for their diagnosis.[2] This biases performance towards analytic processing of biomedical information by promoting *intentional* rather than *incidental* processing of biomedical information - information is processed to *explain* rather than *make* a diagnosis.[32] Being aware of this bias is particularly important in observational studies where the use of automatic processing alone to make a diagnosis is inferred from the lack of analytic processing.

On-line versus post-hoc observations

During think aloud protocols subjects may be asked what they *are* thinking while making a diagnosis or what they *were* thinking when they made a diagnosis: on-line versus post-hoc think aloud. The latter has been criticized as the description of information processing may be modified after the diagnosis has been made.[33] Partly related to the issue of on-line versus post-hoc think aloud, manipulating the amount of data given to subjects prior to asking for a diagnosis is another potential source of performance bias in protocol analysis. When asked to make a diagnosis with few pieces of data, analytic processing appears to be a deductive, or 'diagnosis to data' process, whereas asking subjects to consider all of the available data prior to making a diagnosis tends to make analytic processing an inductive, or 'data to diagnosis', process.[33] If there is any advantage to subcategorizing analytic information processing into deductive versus inductive, protocol analysis appears to be an unreliable way to do this.[34]

Study designs and techniques used to study information processing in this thesis

In this thesis we studied a spectrum ranging from a highly visual domain, wildlife identification, to a complex non-visual domain, electrolyte and acid-base problems. We also included a spectrum of experience ranging from minimal to several years of experience in the domain of study. We used a combination of observational and interventional study designs as we believe that these provide complimentary information on information processing and its association with, or effect on, diagnostic performance. For our think aloud protocols we observed information processing on-line and provided all the information for each case, including contextual information, without forcing subjects to make an early or late diagnosis. We did not try to subcategorize analytic processing as deductive versus inductive. We did not ask subjects to provide a justification for their diagnosis – hoping, therefore, to capture incidental rather than intentional analytic processing. Finally, as previous studies have found that expert performance in medicine is not explained by experts processing more information[9], we focused on quality rather quantity of information processed. For each case we identified relevant concepts *a priori* and studied processing of these concepts in an attempt to separate processing of relevant from irrelevant information.

Research questions

Each of the studies reported in Chapters 2 through 6 addresses a different research question. The questions addresses in each chapter are:

Is analytic processing of relevant biomedical concepts associated with diagnostic performance when solving acid-base and electrolyte problems?

If analytic processing of biomedical concepts contributes in any way to diagnostic performance then it has been suggested that this is more likely to be observed in complex, non-visual domains.[20] In our first study we, therefore, chose to study information processing of both students and experienced physicians in such a domain – acid-base and electrolyte problems. We predicted that if analytic processing of relevant biomedical concepts is helpful when diagnosing electrolyte and acid-base problems then it should be used frequently and have a positive association with diagnostic performance. Alternatively, if analytic processing of relevant biomedical concepts is unhelpful then it should be used infrequently and have either no association or a negative association with diagnostic performance.

What is the contribution of analytic processing of relevant biomedical concepts to diagnostic performance when solving electrolyte and acid-base problems?

Simply demonstrating a statistical association between an independent and a dependent variable does not provide information on the strength of the association, i.e., how much analytic processing contributes to diagnostic performance. Our second study was, therefore, designed to answer questions generated by our first study. The objective was to describe the contribution of analytic processing of relevant biomedical concepts to diagnostic performance of medical students and nephrologists when solving electrolyte and acid-base problems. We considered the four possible contributions: *redundant*, in which case there should be no association with diagnostic performance; *critical*, in which case diagnostic performance should be positively associated with, and dependent upon, analytic processing of relevant biomedical concepts; *detrimental*, in which case analytic processing of relevant biomedical concepts should be negatively associated with performance; and *optional*, in which case diagnostic performance should be positively associated with, but not dependent upon, analytic processing of relevant biomedical concepts.

What is the contribution of biomedical information processing relative to clinical information processing when making a hematological diagnosis?

It has been suggested that the role of biomedical information in making a diagnosis, if any, is secondary to that of clinical information.[21] In our third study we used preference elicitation to assess the utility of biomedical information relative to clinical information when making a hematological diagnosis.[35] We predicted that if, under conditions of free choice, biomedical information is of secondary importance to clinical information, then subjects would preferentially select clinical information early when making a diagnosis and that clinical information bundles would be more likely to be selected as the highest value candidate. If, on the other hand, sequential processing is a function of experimental conditions and/or medical tradition, then the candidate with highest utility would be equally likely to be a clinical or biomedical bundle.

To explore whether the results of our second study were specific to the technique used to study information processing, think aloud, or the domain, electrolyte and acid-base problems, we used preference elicitation to study information processing and evaluated the contribution of analytic processing of biomedical information to diagnostic performance in hematology using the same statistical analyses to those used in our second study.

Does an initial diagnostic hypothesis bias analytic information processing in non-visual domains?

It has been shown that in visual domains, in which automatic processing is thought to predominate, information processing is biased by an initial diagnostic hypothesis.[36] In our fourth study we evaluated the effect of an initial diagnostic hypothesis on analytic information processing. We predicted that if an initial hypothesis biases analytic processing then an incorrect diagnostic hypothesis should reduce diagnostic performance. If, on the other hand, analytic processing is objective and data-driven then diagnostic performance should be unaffected by an initial diagnostic hypothesis. We also assessed whether, in a case where an initial diagnostic hypothesis is rejected, selection of an alternative diagnosis is influenced by previously encountered diagnoses. We predicted that if previous clinical experience influences analytic processing then the diagnosis selected should be encountered more frequency and/or have greater clinical urgency than an initial diagnostic hypothesis that was rejected. But if the search for an alternative diagnosis is objective and data-driven then this should be unaffected by frequency or urgency.

Does training in analytic information processing improve diagnostic performance in a visual domain?

There are conflicting reports in the literature on the contribution of analytic processing to diagnostic performance in visual domains.[25;37;38] In our final study we evaluated the effect of training in analytic information processing on the diagnostic performance of novices in a visual domain. As the study subjects had completed one third of their undergraduate medical training, including training in visual domains such as dermatology, electrocardiogram and chest X-ray interpretation, we felt that they were no longer novices in visual domains in medicine. We, therefore, tested out study hypothesis in a non-medical visual domain, wildlife identification. We considered four possible effects of training in analytic processing to diagnostic performance: *critical*, in which case training in analytic processing should be associated with enhanced performance; *detrimental*, in which case training in analytic processing should be associated with reduced performance; *redundant*, in which case training in analytic processing should not be associated with performance – performance should depend upon the amount of training in automatic processing; and *complementary*, in which case training in analytic processing should enhance the effect of training in automatic processing and vice versa.

Finally, in chapter 7 I have summarized the results of this thesis and discussed how these – and future studies – could be used to shape instructional design and, hopefully, improve diagnostic performance.

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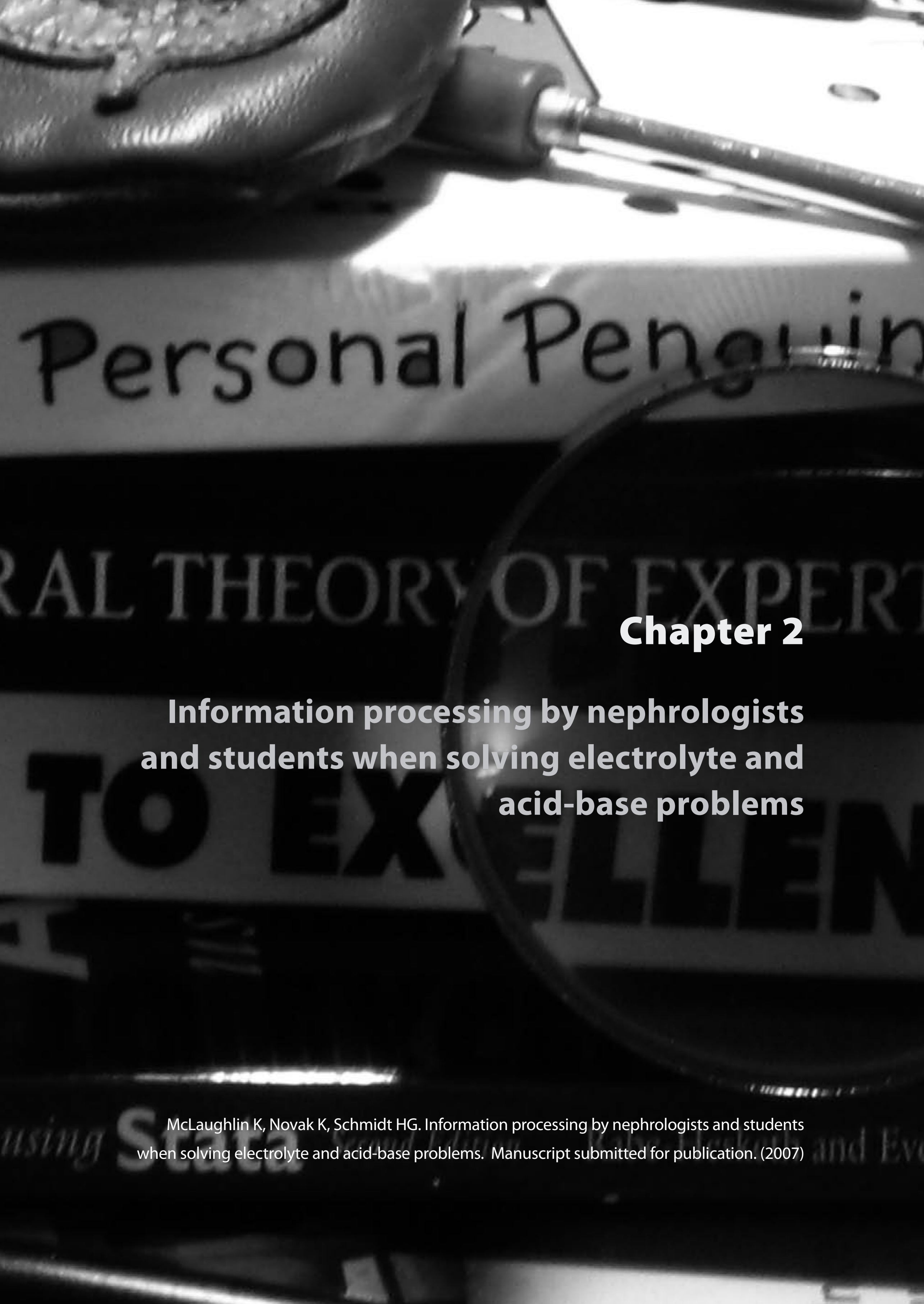

Chapter 2

Information processing by nephrologists and students when solving electrolyte and acid-base problems

McLaughlin K, Novak K, Schmidt HG. Information processing by nephrologists and students when solving electrolyte and acid-base problems. Manuscript submitted for publication. (2007)

ABSTRACT

Introduction. Early studies found that both experienced physicians and students use analytic processing of biomedical information when diagnosing electrolyte and acid-base problems. But adding clinical information reduces this type of processing. Our objective was to evaluate the use of analytic processing of relevant biomedical concepts and its association with diagnostic performance when diagnosing electrolyte and acid-base problems with clinical information. We included experienced physicians and students to assess whether these varied with clinical experience.

*Method***.** We asked 19 nephrologists and 13 first-year medical students to solve four electrolyte and acid-base problems while thinking aloud and analyzed protocols to identify analytic processing of relevant biomedical concepts. We used multiple logistic regression to study the association between processing and diagnostic performance while adjusting for case and clinical experience.

Results. Both nephrologists and students processed at least one relevant biomedical concepts for most cases (81.6% vs. 84.6%, $p = 0.8$). Students had higher success when processing relevant biomedical concepts (72.7% vs. 12.5% for cases with no analytic processing of relevant biomedical concepts, $p = 0.002$). For nephrologists this association was attenuated and non-significant (90.3% vs. 71.4%, $p = 0.08$).

Conclusions. When solving electrolyte and acid-base problems, nephrologists and students both use analytic processing of relevant biomedical concepts. Students had better diagnostic performance if they processed relevant biomedical concepts. The attenuation in nephrologists may be due to clinical knowledge compensating for the lack of biomedical knowledge or encapsulation of biomedical knowledge within clinical knowledge.

Information processing when making a diagnosis

Making a diagnosis may be a rapid, automatic process involving effortless and unconscious connecting of clinical and/or biomedical information of a case to knowledge stored in long term memory. Automatic processing can be supplemented by analytic processing, requiring greater effort and conscious analysis, synthesis and interpretation of clinical and/or biomedical information.[1] Information processing varies between different domains – automatic processing of clinical information predominates in visual domains and analytic processing of biomedical information is used more frequently where interpretation of laboratory information are involved.[2-4] Experimental conditions also influence processing type – analytic processing of biomedical information is increased when data are presented without a clinical context.[4-7]

Information processing as feature of expertise

Free recall studies of expertise in non-medical domains demonstrate a monotonous increase in the amount of information processed from novice to intermediate to expert.[8-10] In medical domains, however, intermediates typically process more information on a case than either novices or experts[11-13]: *the intermediate effect*.[14] But, despite processing less information, experts are still more likely to identify the correct diagnosis.[12] From this observation arose the theory that medical expertise is characterized by qualitative differences in knowledge structure – specifically, the encapsulation of biomedical knowledge within clinical knowledge.[11] Also consistent with the theory of knowledge encapsulation is the finding that, when making a diagnosis, experts preferentially use automatic processing of clinical information but retain the ability to perform analytic processing of biomedical information if this is needed.[5;15;16]

Information processing on electrolyte and acid-base problems

The findings of early studies of information processing on electrolyte and acid-base problems are inconsistent with the knowledge encapsulation theory – experienced physicians (nephrologists) outperform novices and intermediates while processing more, rather than less, biomedical information.[4;17] But adding clinical information to the same lab information reduces analytic processing of biomedical information by another group of experienced physicians – internists – and the intermediate effect is restored.[5] The results of the latter study, therefore, questions the utility of analytic processing of biomedical information when diagnosing electrolyte and acid-base problems if clinical information is also available.

Our objective was to evaluate the use of analytic processing of relevant biomedical concepts and its association with diagnostic performance when solving electrolyte and acid-base problems for which clinical information was also available. We included nephrologists and first year medical students in our study – the former had a minimum of two years clinical experience as practicing nephrologists, while the latter lacked clinical experience – to assess whether utility varied with clinical experience. We predicted that if analytic processing of relevant biomedical concepts is helpful when diagnosing electrolyte and acid-base problems then it should be used frequently and have a positive association with diagnostic performance. Alternatively, if analytic processing of relevant biomedical concepts is unhelpful then it should be used infrequently and have either no association or a negative association with diagnostic performance.

METHODS

This was an observational, cross-sectional study involving 19 nephrologists and 13 first year medical students at the University of Calgary. We recruited students after completion of the sections on electrolyte and acid-base problems in the undergraduate renal course.

Format of the electrolyte and acid-base cases

The four cases were real-life electrolyte and/or acid-base cases. The correct diagnoses for cases 1-4 were: hyponatremia due to primary polydipsia; hyperkalemia due to normal anion gap metabolic acidosis; combined anion gap and normal anion gap metabolic acidosis due to bicarbonate loss from diarrhea and lactic acidosis, along with respiratory acidosis; and combined metabolic alkalosis and respiratory acidosis due to surreptitious vomiting. Each case began with contextual clinical information including presenting symptoms and signs, clinical setting, demographic information, past history and medications. This was followed by laboratory information including serum electrolytes, urine electrolytes and arterial blood gas results. We presented the problems as extended matching questions with a list of 7-13 choices with one single correct answer for each question.

Determination of method of information processing

We determined the method of information processing by analysis of think-aloud protocols. We gave subjects a complete paper version of each case in turn, keeping the order the same for all subjects, and asked them to solve the clinical problem while thinking aloud – verbalizing all thoughts as they arose – and to select the most likely diagnosis. We did not impose time restrictions for completion of the cases and did not ask subjects to justify their diagnosis as we felt that this would bias information processing towards analytic processing.[18] We hoped, therefore, to capture 'incidental' rather than 'intentional' analytic processing of biomedical information while making a diagnosis. We audiotaped and transcribed the protocols for analysis.

Rather than considering both relevant and irrelevant biomedical information, we were primarily interested in whether subjects processed biomedical information that was *relevant* to each case. The relevant concepts for each case were identified as pieces of biomedical information that should be analyzed, synthesized and interpreted during analytic processing. At the University of Calgary the relevant concepts for each clinical presentation are agreed upon by faculty with domain expertise and incorporated into diagnostic schemes which are then given to students.[19] For example, making the diagnosis for Case 1 (primary polydipsia) by analytic processing should involve determining that the 'serum osmolality' is low, 'glomerular filtration rate' is adequate, and that the 'urine osmolality' is low. We identified the relevant biomedical concepts for each case *a priori*. These were: serum osmolality, glomerular filtration rate, and urine osmolality for Case 1; glomerular filtration rate, transtubular potassium gradient and anion gap for Case 2; anion gap, δanion gap:δbicarbonate, and respiratory compensation for Case 3; and effective arterial blood volume, urine pH and respiratory compensation for Case 4. The details of Case 1 are given in Appendix 1 and examples of transcripts with and without analytic information processing of relevant biomedical concepts for this case are given below:

"*Okay, this case is of a young woman complaining of polyuria, nocturia and thirst. No weight loss. Her blood pressure is normal. Her pulse is normal – she is not volume depleted – and we're asked to comment on the sodium which is low at 124. So, first thing, her* ***serum osmolality is low*** *at 264 – so this is hypo-osmolar hyponatremia. Next thing, her* ***urine osmolality is low*** *at 80 mosm/L, which suggests that she is trying to maximally dilute her urine…which means that she's either got inadequate osmole intake or excessive water intake…and the fact that she has thirst and polyuria suggests excessive water intake. So the answer would be primary polydipsia.*" (Analytic processing of two relevant biomedical concepts)

"Okay, so this is a 27 year old female and the problem is hyponatremia and polyuria. There is a very short list of diagnostic possibilities. So, to me, I immediately think of primary polydipsia." (No analytic processing of relevant biomedical concepts)

Two investigators (KM and KN) determined independently whether relevant biomedical concepts were processed for each case and one investigator (KM) determined this on two occasions separated by two weeks. Using the kappa statistic we found 'almost perfect' inter-and intra-rater reliability for determining whether or not relevant biomedical concepts were processed ($\kappa = 0.83$ and 0.91 respectively). Disagreements were resolved by consensus.

Statistical analyses

To assess the use of analytic processing of relevant biomedical concepts associated with clinical experience we used multiple logistic regression to compare its use by nephrologists and students while adjusting for the effect of case. To evaluate the association between analytic processing of relevant biomedical concepts and diagnostic performance we used multiple logistic regression to adjust for the effect of both case and clinical experience (nephrologists versus student). We considered interactions in both models. We used a backward elimination process and compared nested models using the likelihood ratio test. We performed all statistical analyses using Stata 8.0 software (Stata Corporation, College Station, Texas).

Ethical considerations

We received ethical approval from the Conjoint Health Research Ethics Board at the University of Calgary and obtained informed consent from all subjects. We removed the original form of identification (name or student ID) and replaced this with a computer randomized study number to ensure anonymity of subjects and blinding of raters.

RESULTS

The use of analytic processing of relevant biomedical concepts when solving electrolyte and acid-base problems

The proportions of cases in which nephrologists and students processed at least one relevant biomedical concept were 81.6% and 84.6%, respectively. Increased clinical experience was not associated with processing relevant biomedical concepts (adjusted odds ratio 0.8 [0.3, 2.2], $p = 0.6$). Information processing varied between cases – analytic processing of relevant biomedical concepts was used less frequently for Case 2 (adjusted odds ratio 0.3 [0.1, 0.8], $p = 0.018$).

Diagnostic performance when using analytic processing of relevant biomedical concepts

The diagnostic success rate was higher for nephrologists than students (86.8% vs. 63.5%, *p* = 0.003). There was an interaction between clinical experience and the association between analytic processing of relevant biomedical concepts and diagnostic performance (*p* = 0.001). We, therefore, stratified our analysis by clinical experience. For nephrologists there was no significant difference in the success rate of those using and not using analytic processing of relevant biomedical concepts; 90.3% versus 71.4%, respectively (adjusted odds ratio 3.3 [0.7, 15.2], *p* = 0.13). For students the success rate was higher for those processing relevant biomedical concepts; 72.7% versus 12.5% for students who did not use analytic processing of relevant biomedical concepts (odds ratio 18.7 [2.1, 168.1], *p* = 0.002). The Figure shows the diagnostic performance for nephrologists and students associated with analytic processing of relevant biomedical concepts.

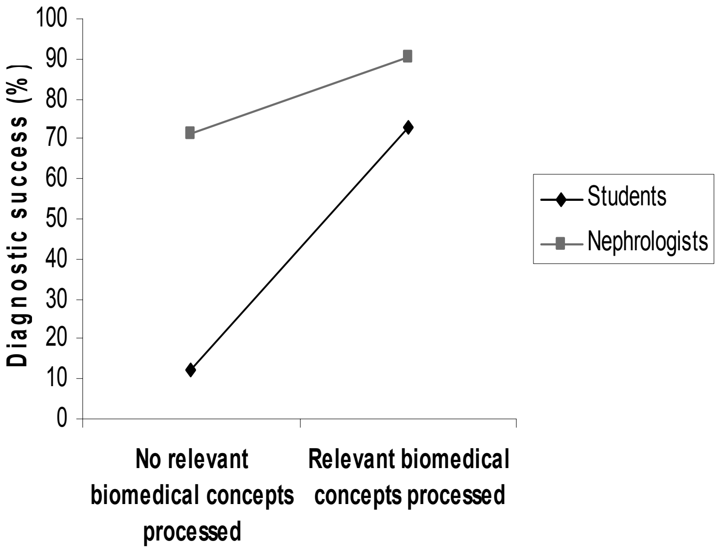

Figure. Diagnostic performance of nephrologists and students when solving electrolyte and acid-base problems with and without analytic processing of relevant biomedical concepts

DISCUSSION

The use of analytic processing of relevant biomedical concepts when solving electrolyte and acid-base problems

We found that at least one relevant biomedical concept was processed when diagnosing most electrolyte and acid-base cases. Despite increased clinical experience, nephrologists were as likely as students to use analytic processing of relevant biomedical concepts. This finding differs from that of studies of similar methodology in other medical domains. For example, when solving problems in gastroenterology, students use analytic processing in approximately 75% of cases, compared to 50% of cases for gastroenterologists.[16] We attributed the higher proportion in our study to electrolyte and acid-base problems being relatively infrequent and challenging, such that it may be difficult to solve them without conscious application of stored biomedical knowledge. But use alone does not imply utility.

Diagnostic performance when using analytic processing of relevant biomedical concepts

The association between analytic processing of relevant biomedical concepts and diagnostic performance varied with clinical experience. Students diagnosing electrolyte and acid-base problems without processing relevant biomedical concepts had significantly poorer performance. Due to limited clinical experience, students were likely dependent upon analytic processing of biomedical information and failure to process relevant biomedical concepts suggests a deficiency in biomedical knowledge. Thus, improving knowledge of relevant biomedical concepts, increasing clinical experience, or both, are potential solutions to poor diagnostic performance of students in this domain.

Despite being used in most cases, the association between analytic processing of relevant biomedical concepts and diagnostic performance was attenuated and non-significant in nephrologists. While the positive trend might suggest that even experienced physicians can enhance diagnostic performance with analytic processing of relevant biomedical concepts, they appear to be less dependent upon this than students. This may be due to the clinical knowledge compensating for deficiencies in biomedical knowledge.[20] Alternatively, rather than being deficient, biomedical knowledge may be encapsulated within clinical knowledge.[12;21] This would allow for tacit application of biomedical knowledge, which would not be detected using think-aloud. Knowledge encapsulation is supported by the results of a previous study in which we found that less than 60% of the relevant biomedical concepts identified in the static knowledge structure of nephrologists were verbalized when solving electrolyte and acid-base problems.[22]

Study limitations

There are some limitations to this study. We considered automatic processing of relevant biomedical concepts as a dichotomous variable – present or absent – and evaluated its association with diagnostic performance. Further studies are needed to quantify its contribution to diagnostic performance: is more processing better than less? Does analytic processing of relevant biomedical concepts *predict* diagnostic performance? The observational design allows us to study associations rather than causality. Thus we can say that processing of relevant biomedical concepts is associated with diagnostic success – we cannot conclude that this causes success. Finally, electrolyte and acid-base problems are challenging problems, replete with biomedical information, so the findings in this domain may not generalize to other domains, such as dermatology, where analytic processing of biomedical information appears to be less relevant.

Conclusions

In conclusion, we found that both nephrologists and students use analytic processing of relevant biomedical concepts to diagnose most electrolyte and acid-base problems. This is associated with improved performance in student but the association is attenuated in experienced physicians – either due to clinical knowledge compensating for deficiencies in biomedical knowledge or encapsulation of biomedical knowledge within clinical knowledge.

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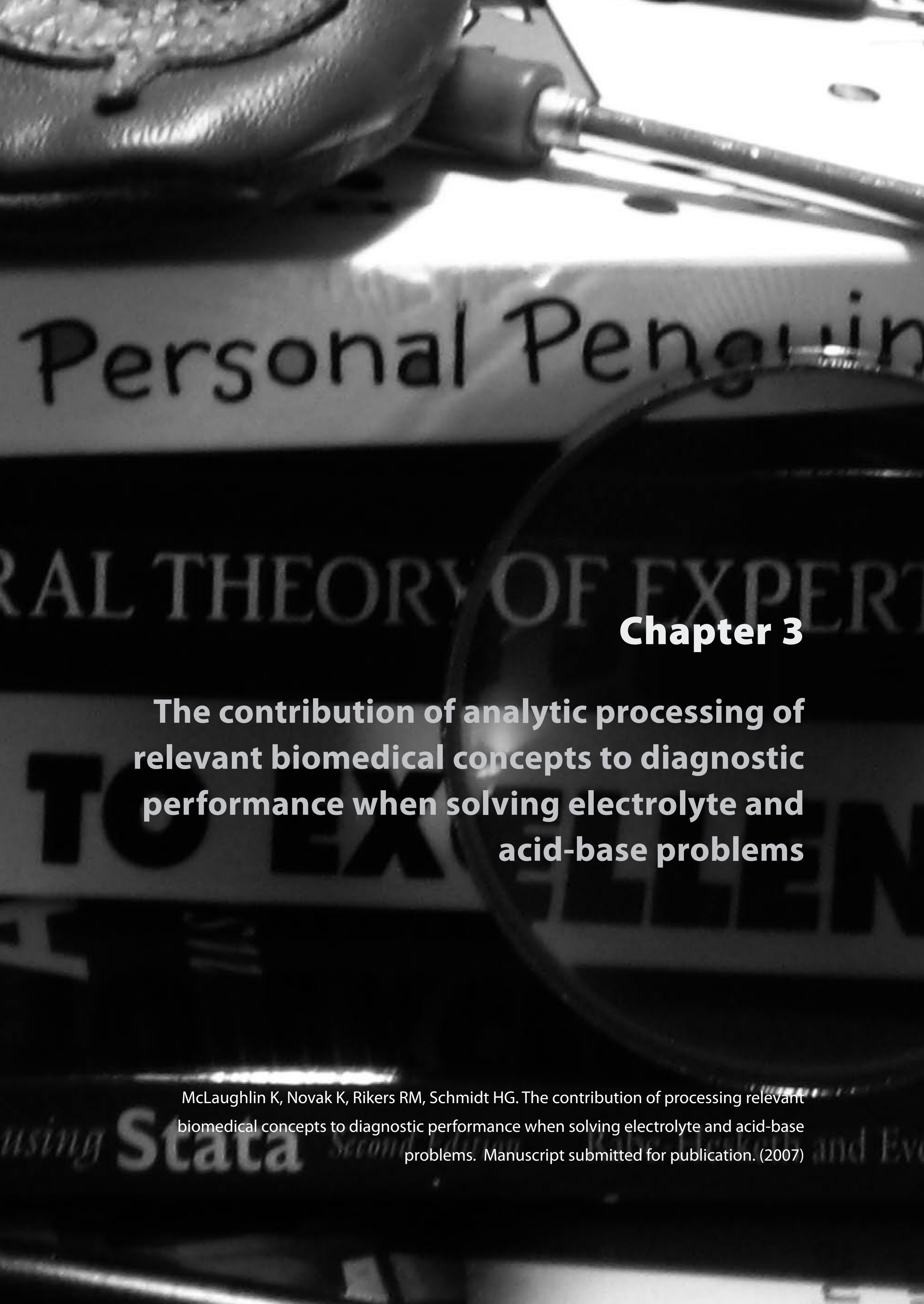

Chapter 3

The contribution of analytic processing of relevant biomedical concepts to diagnostic performance when solving electrolyte and acid-base problems

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ABSTRACT

Introduction. Making a medical diagnosis may involve both automatic and analytic processing of both clinical and biomedical information and appears to vary with clinical experience and domain of study. Our objective was to describe the contribution of analytic processing of relevant biomedical concepts to diagnostic performance when solving electrolyte and acid-base problems. Based upon previous studies we considered four possible descriptions: *redundant*, *critical*, *detrimental* and *optional*.

Method. We asked 13 first-year medical students, with no previous clinical experience, and 19 nephrologists to solve four electrolyte and acid-base problems while thinking aloud and determined analytic processing of relevant biomedical concepts by protocol analysis. We used multiple logistic regression to study the association between analytic processing of relevant biomedical concepts and diagnostic success while adjusting for case, clinical experience and transcript length.

Results. In both groups diagnostic performance increased with processing more relevant biomedical concepts (adjusted odds ratio 3.9 [2.1, 7.2], $p < 0.001$). The number of relevant biomedical concepts processed was a good predictor of diagnostic performance in students (area under ROC curve 0.85 [0.75, 0.96]) but a poor predictor in nephrologists (area under ROC curve 0.67 [0.48, 0.85]).

Conclusions. In clinically inexperienced students analytic processing of relevant biomedical concepts appears to be *critical* to diagnostic performance, suggesting that performance may be enhanced by improving their understanding of relevant biomedical concepts, clinical experience, or both. In experienced physicians the contribution is reduced – *optional* rather than critical – consistent with encapsulation of biomedical knowledge within clinical knowledge through clinical experience.

Information processing when making a medical diagnosis

Diagnosing may be a rapid, automatic process involving effortless and unconscious connecting of clinical and/or biomedical information of a case to stored knowledge. If needed, this may be supplemented by analytic information processing, requiring greater effort and conscious analysis, synthesis and interpretation of clinical and/or biomedical information.[1] Information processing varies between domains: automatic processing of clinical information predominating in visual domains and analytic processing of biomedical information being used more frequently when interpretation of laboratory data are involved.[2-4] Processing also varies with experimental conditions: analytic processing of biomedical information is increased if information is presented without a clinical context.[4-7] Previous studies have reported differences in processing with clinical experience.[7-11] But these studies differ on whether increasing experience (or expertise) is associated with more or less analytic processing of biomedical information.

The contribution of analytic information processing to diagnostic performance

Previous studies evaluating the contribution of analytic processing of clinical and biomedical information to diagnostic performance have produced conflicting results. Patel and colleagues studied first, second and final year medical students diagnosing a case of acute bacterial endocarditis.[11] Students first read and recalled relevant biomedical texts before reading and recalling text describing the patient's problems, providing a diagnosis and explaining this diagnosis on the basis of the underlying pathophysiology. Students applied biomedical knowledge inconsistently or incorrectly when explaining their diagnosis, from which the investigators concluded that clinical and biomedical knowledge exist as distinct entities where processing of clinical information is used to make a diagnosis and analytic processing of biomedical information is used to provide a pathophysiological explanation. In this case the contribution of analytic processing of biomedical information to diagnostic performance could be described as *redundant*.

Lesgold *et al*. studied junior residents, senior residents and expert radiologists diagnosing chest X-rays showing lobectomy, atelectasis and multiple tumours.[8] Correct interpretation involved the explicit use of anatomical and pathophysiological knowledge and experts applied more of this type of knowledge than residents. Gilhooly *et al*. studied registrars, house officers and medical students diagnosing abnormal electrocardiograms.[7] Increasing expertise was associated with more detailed recall and using more clinical and biomedical information when both *making* and *explaining* a diagnosis. The conclusion from these studies was that analytic processing of biomedical information was required for diagnostic success, in which case analytic processing could be described as *critical* to diagnostic performance.

Kulatunga-Moruzi *et al*. studied dermatologists, family medicine specialists and family medicine residents diagnosing dermatology photographs with and without a comprehensive list of clinical features – both for and against the correct diagnosis – designed to facilitate analytic information processing.[12] Diagnostic performance of experienced physicians was reduced with a comprehensive feature list, in which case the contribution of analytic processing could be described as *detrimental*. In a subsequent experiment, however, the same investigators found that using fewer pieces of data – all supporting the correct diagnosis – improved performance of experienced physicians, suggesting that the effect of analytic processing may depend upon both the quantity and quality of information processed.[12]

Boshuizen and colleagues studied second, fourth and fifth year medical students and family physicians diagnosing a case of acute pancreatitis.[13] The groups with clinical experience (fifth year students and family physicians) used fewer biomedical propositions when *diagnosing* the case but more when *explaining* the diagnosis – suggesting that with increasing clinical experience biomedical knowledge is neither lost nor inert, but is encapsulated within clinical knowledge and applied tacitly during information processing. More recent studies by Rikers *et al*. and De Bruin *et al*., using different methodologies, support this finding.[14;15] Verkoeijen *et al*. studied fourth year medical students, clerks and internists diagnosing electrolyte problems with and without a clinical context.[5] Internists used more analytic information processing when clinical context was absent, demonstrating that experienced physicians can, if needed, unfold encapsulated knowledge and apply this overtly, or analytically, when diagnosing. In this case the contribution of analytic processing of biomedical information could be described as *optional*.

Information processing on electrolyte and acid-base problems

We chose the domain of electrolytes and acid-base problems for this study, in part because these represent complex, non-visual tasks in which analytic processing of biomedical information is more likely, but also because of conflicting results of studies in this domain. For example, two studies using the same laboratory data found discrepant results in the amount of analytic processing of biomedical information by experienced physicians, differences that may be due to the addition of contextual data in the latter study, differences in training (Canadian versus Dutch), or differences in the 'expert' groups (nephrologists versus internists).[4;5]

Our objective was to describe the contribution of analytic processing of relevant biomedical concepts to diagnostic performance. To evaluate the potential impact of clinical experience on this we studied first year medical students – who had received teaching in electrolyte and acid-base problems but had no previous clinical experience – and practicing nephrologists with a minimum of two years of clinical experience in nephrology. We considered the four possible contributions described above and predicted the findings based upon each of these descriptions. If *redundant*, there should be no association with performance; if *critical*, performance should be positively associated with, and dependent upon, analytic processing of relevant biomedical concepts; if *detrimental*, there should be a negative association with performance; and if *optional*, performance should be positively associated with, but not dependent upon, analytic processing of relevant biomedical concepts.

METHODS

This was a cross-sectional, observational study of 13 first year medical students and 19 nephrologists at the University of Calgary. We recruited students after completion of the sections on electrolyte and acid-base problems in the undergraduate renal course. The subjects and cases used in this study were the same as those reported in our previous study on electrolyte and acid-base problems (Chapter 2 of this thesis). This study was, therefore, an extension of our previous study and was specifically designed to answer the questions generated by our previous study.

Format of the electrolyte and acid-base cases

We used four real-life electrolyte and/or acid-base cases. The correct diagnoses for Cases 1-4 were: hyponatremia due to primary polydipsia; hyperkalemia due to normal anion gap metabolic acidosis; combined anion gap and normal anion gap metabolic acidosis due to bicarbonate loss from diarrhea and lactic acidosis, along with respiratory acidosis; and combined metabolic alkalosis and respiratory acidosis due to surreptitious vomiting. Each case began with contextual clinical information including presenting symptoms and signs, clinical setting, demographic information, past history and medications. This was followed by laboratory information including serum electrolytes, urine electrolytes and arterial blood gas results. We presented the problems as extended matching questions with a list of 7-13 choices and there was one single correct answer for each question.

Assessment of information processing

To study information processing we analyzed think aloud protocols after audio taping and transcribing the protocols. We gave subjects a complete paper version of each case in turn and asked them to solve the clinical problem while thinking aloud – verbalizing all thoughts as they arose – and to select the most likely diagnosis. We did not ask for an explanation or justification for diagnoses as we felt that this would bias information processing towards analytic processing.[16] As such, we hoped to capture 'incidental' rather than 'intentional' analytic processing of relevant biomedical concepts while making a diagnosis.

Given the discrepant findings of the effect of quantity and quality of information processed we considered both of these factors in our assessment.[12] Consistent with previous studies on electrolyte and acid-base problems, we did not impose time restrictions on solving the cases and used transcript length as a measure of the total information processed.[4] Also, as previous studies have found that expert performance in medicine is not explained by processing of more information[17], we focused on the use of relevant biomedical concepts – identified *a priori* for each case – rather than quantifying the total amount of biomedical information processed, in an attempt to capture analytic processing of *relevant* biomedical information. These concepts were pieces of information that should be analyzed, synthesized and interpreted during analytic processing. At the University of Calgary the relevant concepts for each clinical presentation are agreed upon by faculty with domain expertise and are incorporated into diagnostic schemes that are given to students.[18] For example, making the diagnosis for Case 2 (hyperkalemia due to normal anion gap metabolic acidosis) by analytic processing of relevant biomedical concepts should involve determining that the glomerular filtration rate is adequate, transtubular potassium gradient (TTKG) is appropriate and there is a normal anion gap metabolic acidosis. The details of Case 2 are given in appendix 2 and an example of a transcript, from a nephrologist, where these concepts were correctly interpreted is given below:

"I want to look at the urine handling of potassium. The ***TTKG*** *is 10.1 – so the principle cell* ***is doing what it should be doing in the face of hyperkalemia****, although I note that the urine chloride is low – so there maybe some reduction in the distal delivery of sodium to the cortical collecting duct. The creatinine is 112 – so there is* ***enough glomerular filtration rate*** *for it to be able to filter potassium and lead to its excretion. The likely explanation for hyperkalemia in this setting is due to a shift. So what might cause the shift? Bicarb is 12; she has a* ***normal anion gap acidosis****. This would lead to the buffering of hydrogen ions and displacement of the potassium from the ICF to the ECF causing hyperkalemia which, given the lack of evidence to support cell lysis or any other cause, would suggest that this is the diagnosis here."*

The relevant biomedical concepts were identified for each case *a priori*: serum osmolality, glomerular filtration rate, and urine osmolality for Case 1; glomerular filtration rate, transtubular potassium gradient and anion gap for Case 2; anion gap, δanion gap:δbicarbonate, and respiratory compensation for Case 3; and effective arterial blood volume, urine pH and respiratory compensation for Case 4.

Statistical analyses

To study the association between transcript length, the use of relevant biomedical concepts and diagnostic performance we used multiple logistic regression to allow us to adjust for the effect of case and clinical experience. We considered two and three variable interactions in the model. We used backward elimination and compared nested models using the likelihood ratio test. To measure the strength of the association between both transcript length and the use of relevant biomedical concepts and diagnostic performance we evaluated the ability of these variables to predict performance using area under the Receiver Operating Characteristic (ROC) curve analysis. The advantage of area under the ROC curve analysis is that, rather than choose an arbitrary threshold for estimation of sensitivity and specificity, this analysis considers the whole spectrum of threshold values.[19;20] The area under the ROC curve indicates accuracy of prediction where: 0.5 – 0.6 is 'fail'; 0.6 – 0.7 is 'poor'; 0.7 – 0.8 is 'fair'; 0.8 – 0.9 is 'good'; and 0.9 – 1.0 is 'excellent'. We performed all statistical analyses using Stata 8.0 software (Stata Corporation, College Station, Texas).

Ethical considerations

We received ethical approval from the Conjoint Health Research Ethics Board at the University of Calgary and obtained informed consent from all subjects. We removed the original form of identification (name or student ID) and replaced this with a computer randomized study number to ensure anonymity of subjects and blinding of raters.

RESULTS

The association between information processing and diagnostic performance

There was no difference in either transcript length between students and nephrologists (201 (±107) vs. 235 (±146) words respectively, $p = 0.1$) or number of relevant biomedical concepts used (1.8 (±1.1) vs. 1.8 (±1.2) concepts respectively, $p = 0.8$). There were no interactions in the regression model. The final model is shown in the Table. The diagnostic success rate was higher for nephrologists than students (86.8% vs. 63.5% respectively). For both students and nephrologists diagnostic performance declined with increasing transcript length but improved with increasing use of relevant biomedical concepts. These relationships are shown in Figures 1 and 2 respectively.

Table. Variables associated with diagnostic success on electrolyte and acid-base problems

Variable	Adjusted odds ratio [95% CI]	*p* value
Nephrologist vs. student	7.7 [2.4, 24.8]	0.001
Transcript length (per 100 words)	0.5 [0.3, 0.8]	0.008
Number of relevant biomedical concepts processed	3.9 [2.1, 7.2]	<0.001
Case 2	0.3 [0.1, 1.0]	0.05

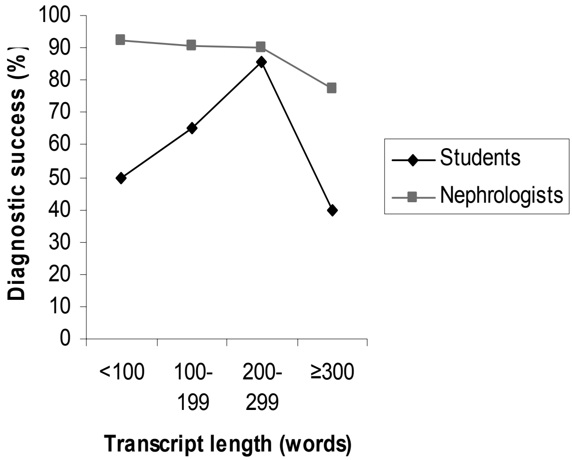


Figure 1. The relationship between transcript length and diagnostic performance for students and nephrologists on electrolyte and acid-base problems

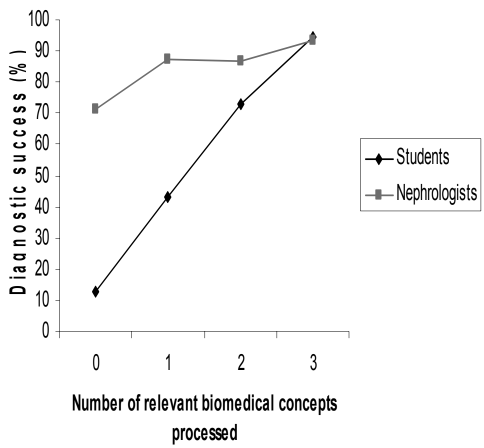
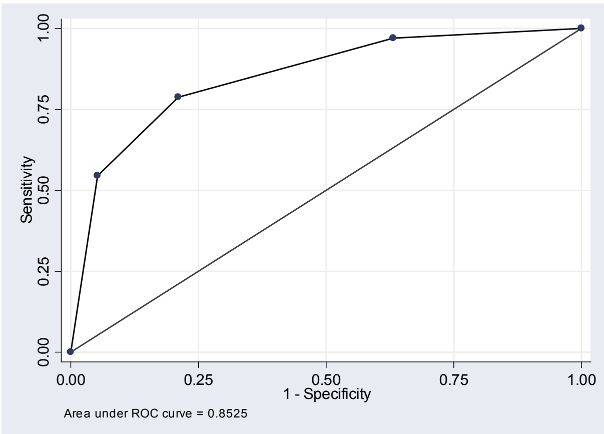


Figure 2. The relationship between use of relevant biomedical concepts and diagnostic performance for students and nephrologists on electrolyte and acid-base problems

Information processing as a predictor of diagnostic performance

Transcript length *failed* to predict diagnostic performance of students (area under ROC curve 0.52 [0.34, 0.70]) and was a *poor* predictor of diagnostic performance of nephrologists (area under ROC curve 0.61 [0.40, 0.82]). The confidence intervals for both of these values cross 0.5 which is the likelihood of an event occurring by chance alone. In students the use of relevant biomedical concepts was a *good* predictor of diagnostic performance (area under ROC curve 0.85 [0.75, 0.96]). For nephrologists, however, the use of relevant biomedical concepts was a *poor* predictor of diagnostic performance (area under ROC curve 0.67 [0.48, 0.85]). The ROC curves for the use of biomedical concepts as predictors of diagnostic performance in students and nephrologists are shown in Figure 3.



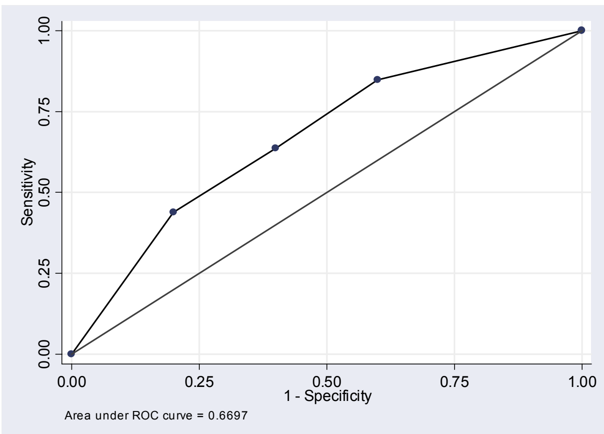


Figure 3. The use of relevant biomedical concepts as a predictor of diagnostic success in students (upper graph) and nephrologists **(lower graph)**

DISCUSSION

The association between information processing and diagnostic performance

Using transcript length as a measure of the total information processed, we found a negative association between this and diagnostic performance for both students and nephrologists – processing more information was associated with poorer performance. A recent study, where the amount of information processes was manipulated, also found that processing more information reduced the performance of practicing physicians.[12] The authors explained this finding as analytic processing inhibiting automatic processing of experienced physicians. But our study subjects could process as much or as little information as they chose – and the negative association was not limited to experienced physicians. A more likely explanation, therefore, for our result is that failure to generate a satisfactory hypothesis leads to continued information processing and poorer diagnostic performance.[21]

For both students and nephrologists there was a positive association between processing relevant biomedical concepts and diagnostic performance, i.e., the more concepts they processed the better their performance. This finding is inconsistent with the contribution of analytic processing of relevant biomedical concepts being either *redundant* or *detrimental*. It is, however, consistent with the contribution of analytic processing being either *critical* or *optional*.

Information processing as a predictor of diagnostic performance

Despite a statistically significant association with diagnostic performance, ROC analysis demonstrated that transcript length was not a good predictor of diagnostic performance in either students or nephrologists. The number of relevant biomedical concepts processed was a good predictor of diagnostic performance in students – suggesting that analytic processing of relevant biomedical concepts is *critical* to diagnostic performance. Having no previous clinical experience, students were likely dependent upon processing of biomedical information and failure to process relevant biomedical concepts suggests a deficiency in biomedical knowledge.

In nephrologists the number of relevant biomedical concepts processed was a poor predictor of performance, implying that the contribution of analytic processing of relevant biomedical concepts to performance is less than in students. This is inconsistent with analytic processing of relevant biomedical concepts being *critical*, as is the observation that nephrologists outperformed student while processing the same number of relevant biomedical concepts. *Optional*, therefore, appears to be the most appropriate adjective for the contribution of analytic processing of relevant biomedical concepts to diagnostic performance in experienced physicians. This finding is consistent with Schmidt and Boshuizen's theory of knowledge encapsulation: experts diagnose by applying clinical knowledge – within which biomedical knowledge is encapsulated – but can also, if the task demands, unfold encapsulated knowledge and apply biomedical information analytically.[9]

Teaching implications

Finding that diagnostic performance of medical student on electrolyte and acid-base problems appears to be critically dependent upon analytic processing of biomedical information suggests that performance could be enhanced by improving understanding and application of relevant biomedical concepts. Alternatively, increasing clinical knowledge, through clinical experience, may reduce dependence upon analytic processing of biomedical information – as appears to be the case with experienced physicians – and allow students to solve these problems by processing clinical information. These strategies are, of course, not mutually exclusive and the combination may be better than either alone.

The performance of experienced physicians on electrolyte and acid-base problems appears less dependent on analytic processing of biomedical information than that of students. But the positive association between the number of relevant biomedical concepts processed and diagnostic performance suggests that this group may also benefit from improved understanding and application of these concepts. Previous studies have also shown that while experts typically use automatic processing of clinical information when solving routine problems, diagnostic performance on complex problems may be improved by analytic information processing.[7;22;23]

Study limitations

There are some limitations to this study. The observational cohort design allows us to study associations rather than test hypotheses or study causality. Thus we can only say that we found an association between analytic processing of relevant biomedical concepts and diagnostic performance; we cannot conclude that processing relevant biomedical concepts *caused* the improved diagnostic performance. This study only included first year medical students and nephrologists and we cannot comment, therefore, on the association between information processing and diagnostic performance in clerks, residents or other groups of experienced physicians. Finally, the findings in the domain studied, electrolytes and acid-base problems, may not generalize to other clinical domains.

Conclusions

In this study we found a negative association between the amount of information processed and diagnostic performance, consistent with the explanation that processing continues until a satisfactory hypothesis has been generated. Diagnostic performance improved with the use of more relevant biomedical concepts, suggesting that quality of information processed is more important than quantity. The contribution of analytic processing of relevant biomedical concepts to diagnostic performance decreased with clinical experience, consistent with encapsulation of biomedical knowledge within clinical knowledge as a result of clinical experience.[9]

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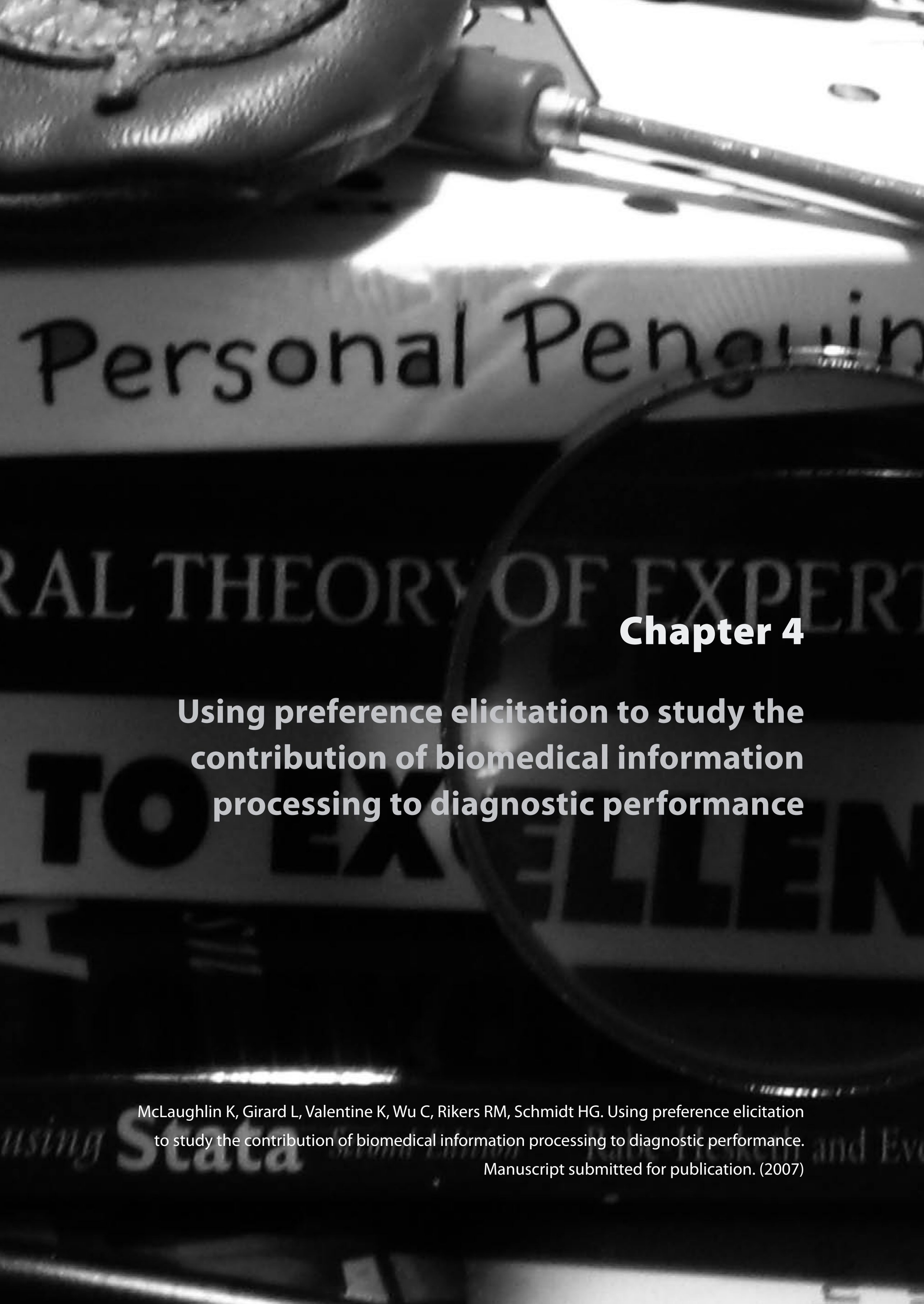

Chapter 4

Using preference elicitation to study the contribution of biomedical information processing to diagnostic performance

McLaughlin K, Girard L, Valentine K, Wu C, Rikers RM, Schmidt HG. Using preference elicitation to study the contribution of biomedical information processing to diagnostic performance. Manuscript submitted for publication. (2007)

ABSTRACT

Background. Biomedical information processing is considered secondary to clinical information processing when making a medical diagnosis, both in terms of when it is processed and the contribution that it makes to performance. Our objectives were to assess the relative utilities of biomedical and clinical information and to evaluate the contribution of biomedical information processing to diagnostic performance.

Methods. We used preference elicitation to study information processing by 27 clerks and 13 residents while diagnosing two hematology cases. We compared the relative utilities of clinical and biomedical information and used multiple logistic regression to evaluate the association between biomedical information processing and diagnostic performance while adjusting for clinical information processing, case and clinical experience. We used area under the receiver operating characteristic (ROC) curve analysis to evaluate biomedical information processing as a predictor of performance.

Results. Clerks and residents were equally likely to ascribe the highest utility to a biomedical as a clinical bundle. Biomedical information processing was positively associated with diagnostic success (adjusted odds ratio 1.40 [1.05, 1.85], $p = 0.02$), but was a poor predictor of success (area under the ROC curve of 0.64 [0.51, 0.76]).

Conclusions. When solving hematology problems biomedical and clinical information have equal utility. Biomedical information processing is positively associated with diagnostic performance, suggesting that this is an effective strategy when solving hematology problems. The fact that biomedical information processing is a poor predictor of diagnostic performance is likely due to the concomitant contribution of clinical information processing to performance.

Information processing when making a diagnosis

Making a medical diagnosis involves connecting clinical and/or biomedical information of a case to knowledge stored in long term memory. Observational studies of information processing have suggested that making a diagnosis begins with generating an initial diagnostic hypothesis by processing clinical information, including presenting symptoms and signs, along with contextual information such as clinical setting, age, gender, past history and disease-specific risk factors.[1-3] If this has resulted in a satisfactory diagnosis then information processing may stop at this point. If a satisfactory diagnosis has not been reached then biomedical information may be processed to test the initial hypothesis or to generate alternative hypotheses. This description of information processing implies that when making a diagnosis, biomedical information is secondary to clinical information, both in terms of when it is processed and its relative contribution. It is unclear, however, to what extent this apparent relationship is a function of the experimental conditions used to study information processing and/or medical tradition that teaches the sequence of presenting history and physical prior to the results of investigations.

The contribution of biomedical information processing to diagnostic performance

There are contradictory reports in the literature on the contribution of biomedical information processing to diagnostic performance. At one extreme, Patel *et al.* propose that clinical and biomedical information exist as two distinct entities, such that clinical information is processed to make a diagnoses and biomedical information is processed to provide a pathophysiological explanation.[4] In this case the contribution of biomedical information processing would be described as *redundant*. At the other extreme, Lesgold, *et al.* and Gilhooly, *et al.* found that experts processed more biomedical information than non-experts, particularly on tasks of greater difficulty, and conclude that diagnostic success is dependent upon processing of biomedical information.[5;6] In this case the contribution of biomedical information processing would be described as *critical.* While some of the variation in the contribution of biomedical information processing to diagnostic performance may relate to differences in clinical experience and the clinical domains studied, there is also evidence that studies using think aloud to study information processing are prone to performance bias related to the experimental conditions and think aloud methodology used.[7;8] Asking for a pathophysiological explanation, for example, introduces a performance bias towards 'intentional' processing of biomedical information.[9] Varying the amount of clinical information provided also influences biomedical information processing. [10;11]

Studying information processing by preference elicitation

Preference elicitation is a technique that has been used to study information processing in math and engineering but, thus far, has not been used to study medical information processing.[12-14] There are several variations on the technique (see reference[12] for a detailed description) and each involves organizing information into information bundles and then studying the relative utility that subjects ascribe to these bundles. The framework for ascribing utility may be one of *combinatorial auction*, where each bundle is ascribed a value relative to the other bundles, *decision analysis*, where a decision is made on each individual bundle (accept or reject), or *incremental querying*, where the relative utility are implied from rank order – the first bundle requested has the highest utility, etc. The advantage of the latter is that it allows for conditional utility, i.e., the value of bundle Y depends upon the result of processing bundle X. Incremental querying could be used, for example, to determine information preferences when trying to identify the animal that is hurtling down the hillside towards you when you are hiking in the mountains. The order of information bundles, beginning with the most valuable, might be: *location* / *size* / *colour* / *hump*. Note the denomination relationship between these bundles, with location having the highest utility – the large brown animal in the Scottish Highlands is likely to be a friendly dog compared to a grizzly bear in the Canadian Rockies.

Using preference elicitation to study information processing when making a diagnosis

Unlike the typical experimental conditions used to study information processing when making a diagnosis, where subjects are given all the information up front, making a diagnosis in real life frequently involves incremental querying, where selecting a new piece of clinical or biomedical information depends upon the interpretation of previous pieces. As such, preference elicitation appears to have face validity for studying information processing in medicine. Forcing subject to make conscious decisions about information they wish to process likely biases information processing towards analytic processing – so preference elicitation is best used to study *what* type of information is processed rather than *how* it is processed. Preference elicitation does not require subjects to justify their diagnosis and encourages subjects to use as few pieces of information as possible when making a diagnosis, both of which should discourage superfluous information processing. By assigning utilities to different information bundles it is possible to study denomination relationships between bundles and, thus, their relative contribution to the process of making a diagnosis. In addition, this may also provide an evaluation of the association between process and outcome, such as between processing an individual bundle, or groups of bundles, and diagnostic performance.

In this study our first objective was to assess the utility of biomedical information relative to clinical information when making a diagnosis. We predicted that if, under conditions of free choice, biomedical information is of secondary importance to clinical information, then subjects would preferentially select clinical information early when making a diagnosis and that clinical information bundles would, therefore, be more likely to be selected as the highest value candidate. If, on the other hand, sequential processing is a function of experimental conditions and/or medical tradition, then the candidate with highest utility would be equally likely to be a clinical or biomedical bundle. We chose, as our area of study, two clinical presentations in hematology as these presentations are sufficiently frequent that we would expect the subjects in this study, clerks and first year internal medicine residents, to have encountered several cases of each presentation and, therefore, have some stored clinical knowledge that could be used to process clinical information. At the same time clinical presentations in hematology also typically involve interpretation of lab information, thus allowing us to study biomedical information processing.[10]

Our second objective was to describe the relative contribution of biomedical information processing to diagnostic performance. We considered four possible contributions of biomedical information processing and predicted the findings based upon each of these descriptions. If biomedical information processing is *redundant* then there should be no association with diagnostic performance. If biomedical information processing is *critical* then diagnostic performance should be positively associated with, and dependent upon, biomedical information processing. If biomedical information processing is *detrimental* then this should be negatively associated with diagnostic performance. The final contribution of biomedical information processing that we considered was *optional*. This situation may arise, for example, if biomedical information processing makes a positive contribution to diagnostic performance but the availability of other types of information, such as clinical information, means that performance is not critically dependent upon biomedical information processing. In this case we predicted that diagnostic performance should be positively associated with, but not dependent upon, biomedical information processing.

METHODS

Study design and subjects

This was a cross-sectional observational study. Subjects were 27 clerks and 13 first year Internal Medicine residents at the University of Calgary. The University of Calgary has a three year undergraduate curriculum in which the final year comprises clinical clerkship rotations. During this time each student has a mandatory three month rotation in internal medicine.

Internal medicine residency training includes three core years of internal medicine prior to subspecialization.

The settings for the study was a 'study station' on both the formative OSCE at the midpoint of the clerkship rotation and at the completion of the first year of the internal medicine residency training program. The station format was identical for clerks and residents and the time for each station was 12 minutes. We invited all clerks and residents to participate and all accepted this invitation. We received ethical approval from the Conjoint Health Research Ethics Board at the University of Calgary and obtained informed consent from all subjects prior to entry into the study.

Preference elicitation protocol

The format of the study was a simulated casual consultation with an internal medicine colleague who was requesting help with the diagnosis of two patients, in whom the clinical presentations were anemia and bleeding diathesis respectively. Each case was read out to the study subject. The case for anemia is shown below:

You are enjoying your morning coffee break in the doctors' lounge when I, a general internist, ask if I can discuss a patient with you. I have been investigating an outpatient with hemoglobin of 98g/L and I am not sure as to the cause of the anemia. I would like your assistance with the diagnosis and I would like you to get to the diagnosis using as few pieces of information as possible. The patient has been thoroughly investigated and I can give you any clinical or lab information that you wish.

We grouped the information for each case into ten information bundles – five clinical and five biomedical. We applied the same labels to the clinical bundles for each case: demographics; associated symptoms/signs; past history; family history; and disease-specific risk factors (including medications). We changed the labels on the biomedical bundles for each case as the appropriate laboratory investigations were different for each case. The information bundles for anemia are shown in Appendix 3.

We gave subjects the list of information bundle labels and invited them to request one of the bundles, at which point we gave them all the information contained within this bundle. This process was repeated until the subject stated that they had completed the task and provided their final diagnosis. We recorded all the information bundles requested and the order in which they were requested. We identified the first bundle requested as the highest value candidate and calculated the total number of clinical and biomedical bundles requested for each case. We allowed re-requesting of bundles and coded this as a new request (hence, the number of bundles requested could exceed ten despite their being only ten bundles available). The recording sheet for the anemia case is shown in Appendix 4. All tasks were completed within the 12 minutes allowed for the OSCE station. We determined the correct diagnosis (and acceptable synonyms) for each case by piloting the questions to subspecialists in hematology and internal medicine (KV and CW respectively).

Statistical analyses

To assess the relative utility of clinical and biomedical information processing when making a diagnosis we calculated the proportion of highest value candidates that were clinical and biomedical information bundles for each case. We used multiple logistic regression to study the association between diagnostic success and the number of biomedical bundles processed while adjusting for the number of clinical bundles processed, clinical experience (clerk vs. resident) and case. We also considered possible interactions variables in the logistic regression model. A backward elimination process was performed and nested models compared using the likelihood ratio test.

To measure the strength of the association between processing of biomedical bundles and diagnostic performance we evaluated processing of biomedical bundles as a predictor of diagnostic success using area under the receiver operating characteristic (ROC) curve analysis. The advantage of area under the ROC curve analysis is that, rather than choose an arbitrary threshold for estimation of sensitivity and specificity, this analysis considers the whole spectrum of threshold values.[15;16] The area under the ROC curve indicates accuracy of prediction where: 0.5 – 0.6 is 'fail'; 0.6 – 0.7 is 'poor'; 0.7 – 0.8 is 'fair'; 0.8 – 0.9 is 'good'; and 0.9 – 1.0 is 'excellent'. We performed all statistical analyses using Stata 8.0 software (Stata Corporation, College Station, Texas).

RESULTS

Utility of biomedical information when making a diagnosis

For the anemia case 56% [40, 72] of subjects selected a clinical bundle as the highest value candidate compared to 36% [20, 52] for the bleeding diathesis case. In neither case was this proportion significantly different from that expected by chance alone (50%, $p = 0.4$ and $p = 0.08$, respectively). There was no difference in the proportion of clerks or residents selecting either a clinical or biomedical bundle as the highest value candidate.

Contributions of biomedical information processing to diagnostic performance

The diagnostic success rate did not differ significantly between clerks and residents (50.9% vs. 53.8%, p = 1.0) and did not differ significantly between the two cases (p = 0.4). There were no significant interactions in the model. In the final model both the total number of biomedical bundles and clinical bundles were associated with diagnostic success. The odds of diagnostic success increased with increasing biomedical information processing (adjusted odds ratio 1.40 [1.05, 1.85], p = 0.02) but decreased with increasing clinical information processing (adjusted odds ratio 0.75 [0.60, 0.94], p = 0.01). The relationship between the number of bundles requested and diagnostic performance is shown in Figure 1.

Biomedical information processing as predictor of diagnostic performance

The number of biomedical bundles processed was a *poor* predictor of diagnostic success. The area under the ROC curve of 0.64 [0.51, 0.76], with a value of 0.5 representing the likelihood of success occurring by chance alone. The ROC curves for biomedical information processing as predictors of diagnostic performance are shown in Figure 2.

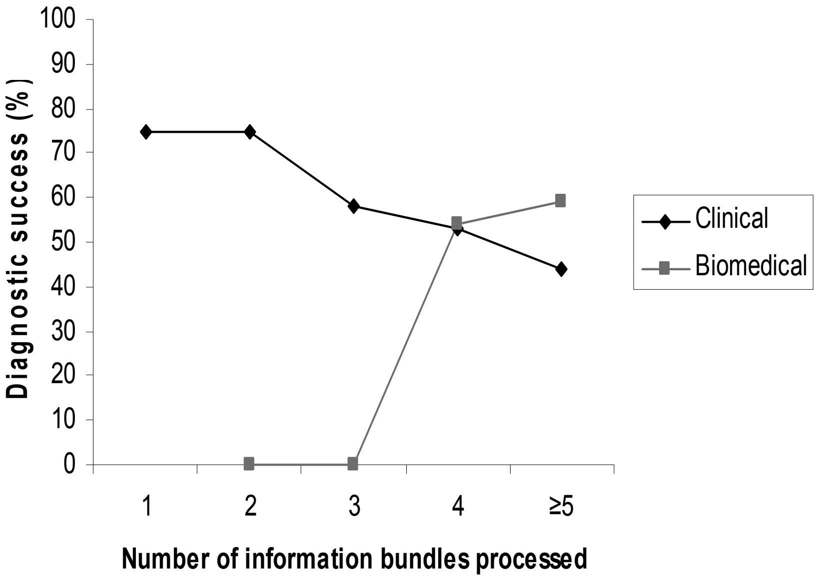

Figure 1. The association between the number of clinical and biomedical information bundles processed and diagnostic performance

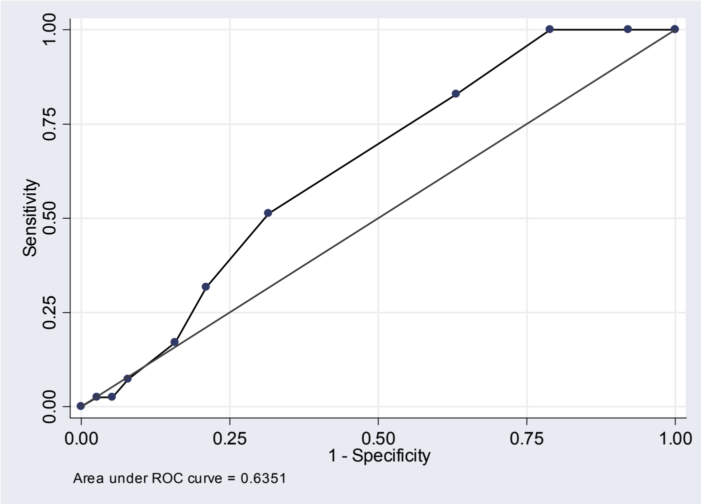

Figure 2. Processing of biomedical information bundles as a predictor of diagnostic success

DISCUSSION

Utility of biomedical information when making a diagnosis

In this study we found that when making a diagnosis clerks and residents were as likely to ascribe the highest utility to a biomedical bundle as a clinical bundle. This finding is inconsistent with information processing being sequential, i.e., processing of clinical information generating a hypothesis that may, or may not, then be tested by processing biomedical information, and argues against biomedical information being of secondary importance to clinical information when making a diagnosis, at least in clerks and residents when solving hematology problems.[1-3] Rather, this finding would support flexibility of information processing and coordination of processing of clinical and biomedical information such that both can be used to generate and test hypotheses.[17]

Contribution of biomedical information processing to diagnostic performance

We found a significant positive association between biomedical information processing and diagnostic performance. This finding is inconsistent with the contribution of biomedical information processing to diagnostic performance being either *redundant* or *detrimental*. These results are consistent with those of a recent study in which we also found a significant positive association between analytic processing of key biomedical concepts and diagnostic performance on electrolyte and acid-base problems in both first year medical students and practicing nephrologists (Chapter 3 of this thesis). The likely explanation for this finding is that solving problems in hematology, as with nephrology, frequently requires analysis and interpretation of laboratory data which, in turn, requires application of biomedical knowledge, such as knowledge of physiology and pathophysiology. The positive association between biomedical information processing and diagnostic performance would suggest that this is an effective information processing strategy when solving hematology problems.

In this study we also found a negative association between clinical information processing and diagnostic performance, i.e., processing more clinical information was associated with poorer diagnostic performance. This is also similar to our previous study where we found a negative association between the total amount of information processed and diagnostic performance (Chapter 3 of this thesis). In a recent study by Kulatunga-Moruzi, *et al.*, where the amount of information processes was manipulated, it was also shown that processing more clinical information lead to reduced performance of practicing physicians.[18] In this it was suggested that the reason for this effect was due to analytic processing inhibiting automatic processing that is typical of experienced physicians. In our study, however, subjects had limited clinical experience and were free to process as much or as clinical little information as they chose. As such, a more likely explanation for this association in our study is that failure to generate a satisfactory hypothesis leads to continued clinical information processing and poorer diagnostic performance.[19]

Biomedical information processing as predictor of diagnostic performance

The fact that the number of biomedical bundles processed was a *poor* predictor of diagnostic success suggests that diagnostic performance is not critically dependent upon this, and the best description of the contribution of biomedical information processing to diagnostic performance is, therefore, *optional*. We believe the most likely explanation for this finding is that, despite limited clinical experience, the subjects in this study were able to process clinical information successfully, thus reducing the reliance on biomedical information processing.[20]

Study limitations

This study has some limitations, such as the limited number of subjects, clinical presentations, and tasks within each presentation. The subjects in this study had a narrow range of clinical experience and the findings may not generalize to other groups, such as experienced physicians. In using preference elicitation we focused on whether or not information bundles were processed, not how well they were processed, which is obviously important. By lacking the physical presence of a real patient, with the additional clinical information that this provides, and forcing incremental querying, it is likely that preference elicitation biases information processing away from automatic processing and towards analytic processing. This situation is, however, not unrealistic in medicine as physicians are frequently asked to contribute to making a diagnosis in this way, such as providing telephone advice to a colleague.

The observational design allows us to study associations rather than test hypotheses or study causality. Thus we can only say that we found an association between biomedical information processing and diagnostic performance; we cannot conclude that biomedical information processing caused improved diagnostic performance. To test the latter a study in which students were randomly allocated pieces of clinical and biomedical information would be needed.

Despite these limitations, however, we believe that preference elicitation has a potential role in studying information processing when making a medical diagnosis and the information provided by this may be relevant to those involved in medical education.

Conclusions

In this study using preference elicitation we found that biomedical information has equal utility to clinical information when solving problems in hematology. Biomedical information processing had a significant, positive association with diagnostic performance, suggesting that this is an effective strategy when solving problems in hematology. Biomedical information processing was not, however, a good predictor of diagnostic performance, likely due to the additional contribution of clinical information processing. Further studies are needed to evaluate the use of preference elicitation as a tool to study information processing in medicine.

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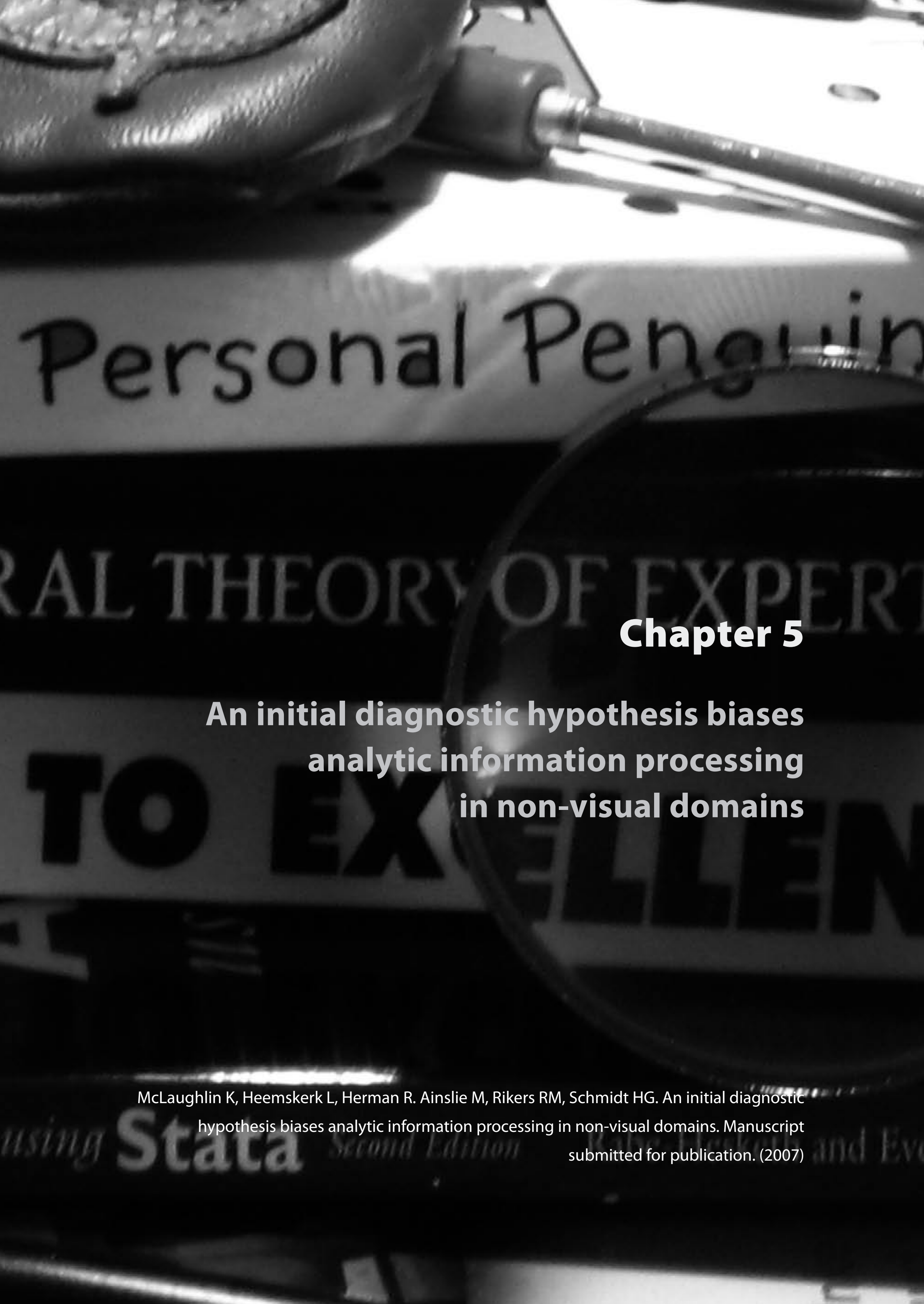

Chapter 5

An initial diagnostic hypothesis biases analytic information processing in non-visual domains

McLaughlin K, Heemskerk L, Herman R. Ainslie M, Rikers RM, Schmidt HG. An initial diagnostic hypothesis biases analytic information processing in non-visual domains. Manuscript submitted for publication. (2007)

ABSTRACT

Background. Previous studies have shown that an initial diagnostic hypothesis biases automatic information processing. It is unclear if an initial hypothesis has a similar effect on analytic information processing. Our first objective was to study the effect of an initial diagnostic hypothesis on analytic processing. Our second objective was to assess the effect of clinical experience on analytic information processing by evaluating the effect of clinical frequency and urgency of an alternative diagnosis on diagnosis selection.

Methods. During a 12 minute OSCE station, 19 subspecialty medical residents diagnosed the cause of three clinical presentations: dyspnea, headache and chest pain. Subjects were randomly allocated cases for which an initial hypothesis was correct vs. incorrect. For cases with an incorrect initial hypothesis, the alternative diagnoses varied with respect to frequency and urgency relative to an initial diagnostic hypothesis.

Results. All correct initial hypotheses were retained compared to 10.9% of incorrect hypotheses. All cases with a correct initial hypothesis were diagnosed correctly compared to 65.2% of cases with an incorrect hypothesis (risk ratio 1.5 [1.2, 1.9], $p = 0.02$). Clinical frequency and urgency were not associated with alternative diagnosis selection.

Discussion. Our results suggest that an initial diagnostic hypothesis biases analytic information processing. The data used to reject an initial hypothesis appears to drive selection of an alternative hypothesis. Further studies aimed at increasing the likelihood of generating a correct initial hypothesis and/or debiasing an initial hypothesis are needed.

Information processing when making a medical diagnosis

Making a diagnosis frequently requires only automatic information processing, involving effortless and unconscious connecting of clinical and/or biomedical information of a case to stored knowledge. Where needed, this may be supplemented by analytic information processing, requiring greater effort and conscious analysis, synthesis and interpretation of clinical and/or biomedical information.[1] Information processing appears to vary with the domain of study; automatic processing of clinical information predominating in visual domains and analytic processing of biomedical information being used more frequently when interpretation of laboratory information are involved.[2-4] Processing also varies between experimental conditions with analytic processing of biomedical information being more common when uncontextualized information are presented.[4-7] Several studies have also suggested that information processing changes with clinical experience, although they differ on whether increasing experience leads to more or less analytic information processing. [7-10]

The effect of an initial diagnostic hypothesis on automatic information processing

Most studies assessing automatic processing have involved visual tasks, such as diagnosing rashes or abnormalities in physical appearance, or identifying abnormalities on an electrocardiogram or chest X-ray.[6;11-13] Initial studies found that when subjects are given a correct initial diagnostic hypothesis they are more likely to identify correct features and make the correct diagnosis, which was interpreted as an initial hypothesis focusing the search for correct features.[11;13;14] More recent studies show that when given an incorrect hypothesis, subjects tend to miss correct features, identify incorrect features, and are more likely to make the wrong diagnosis.[12] Thus, an initial diagnostic hypothesis biases automatic processing by effecting both *identification* and *interpretation* of clinical features.

Analytic information processing: data-driven, diagnosis-driven, or both?

While studies on automatic processing provide consistent evidence that information is processed with an initial diagnostic hypothesis in mind, there is less agreement on analytic processing. Early studies proposed that analytic processing by experienced physicians involves diagnosis-driven processing, in the form of hypothetico-deductive reasoning.[15] Later studies, however, suggested that analytic processing by experienced physicians involves data-driven processing, in the form of inductive reasoning.[16;17] Differences in think-aloud methodologies in these studies may partly explain the inconsistent results.[18] If analytic processing truly involves data-driven processing of information then this should be objective and free from bias by diagnostic hypotheses, irrespective of whether these are generated early or late. Alternatively, if processing is diagnosis-driven then diagnostic hypotheses should influence information processing.

In this study we assessed two potential sources of bias of analytic information processing. The first was an initial diagnostic hypothesis resulting from automatic processing, which is relevant given that, in real life, it is likely impossible to prevent automatic processing and generation of an initial diagnostic hypothesis prior to analytic processing.[19;20] The second was diagnostic hypotheses generated during analytic processing as a result of previous clinical experience. If analytic processing is biased by previously encountered diagnoses then the frequency with which a diagnosis is encountered in clinical practice, or the clinical urgency associated with a diagnosis, may influence information processing such that more frequent and/or urgent diagnoses are chosen preferentially.

We chose as our study subjects medical subspecialty residents who had completed their core training in internal medicine and were about to receive certification to practice as independent physicians. We felt that this group would be proficient in analytic information processing in commonly encountered clinical presentations and, at the same time, have sufficient clinical experience to have encountered both frequent and urgent diagnoses within each clinical presentation. To facilitate analytic information processing after the initial diagnostic hypothesis we forced subjects to request additional clinical and laboratory information, one piece at a time, and presented verbal rather than visual information.

Our first objective was to evaluate the effect of an initial diagnostic hypothesis on analytic information processing. We predicted that if an initial hypothesis biases analytic processing then an incorrect diagnostic hypothesis should reduce diagnostic performance. If, on the other hand, analytic processing is objective and data-driven then diagnostic performance should be unaffected by an initial diagnostic hypothesis. We only considered the effects of a correct vs. incorrect initial hypothesis and did not include a control group without an initial hypothesis. There were two reasons for this. First, it may not be possible to prevent generation of an initial hypothesis[19;20] – so the control group would likely create their own hypotheses over which we had no influence. Second, a previous study has shown that trying to prevent subjects generating an initial diagnostic hypothesis impairs their diagnostic performance.[21]

Our second objective was to assess whether, in a case where an initial diagnostic hypothesis is rejected, selection of an alternative diagnosis is influenced by previously encountered diagnoses. We predicted that if previous clinical experience influences analytic processing then the diagnosis selected should be encountered more frequency and/or have greater clinical urgency than an initial diagnostic hypothesis that was rejected. Alternatively, if the search for an alternative diagnosis is objective and data-driven then this should be unaffected by frequency or urgency.

METHODS

Subjects

Study subjects were 19 fourth year medical subspecialty residents. Each resident had completed three core years in the Internal Medicine Residency Training Program at the University of Calgary and was within three months of taking the Royal College of Physicians and Surgeons of Canada certification examination in Internal Medicine. We invited all residents to participate and obtained written informed consent prior to their entry into the study. The Conjoint Research Ethics Board at the University of Calgary gave ethical approval for the study.

Study setting

We performed this study as part of a formative OSCE given to fourth year medical subspecialty residents as preparation for the certification examination in Internal Medicine. The study station was 12 minutes long and began by a rural Emergency Room (ER) physician calling the resident and requesting advice on the diagnoses of three patients presenting to the ER. The clinical presentations for the three cases were dyspnea, headache and chest pain. The order of the clinical presentations was the same for each resident and four minutes were spent on each case. After four minutes the resident was asked to provide the most likely diagnosis for this case.

Creation of cases

There were two components to each case: *provided* information and *requested* information. The provided information was designed to facilitate the generation of an initial diagnostic hypothesis by automatic information processing and included presenting symptom, clinical setting (ER), demographic information, past history, and disease-specific risk factors in addition to the diagnosis felt most likely be the ER physician. The requested information comprised all additional clinical and laboratory information of the case.

Subjects were told beforehand that they could request additional information from history, physical examination or investigations. They were told that due to technical difficulties they could not see X-rays of electrocardiogram tracings but, instead, were given an accurate description (without diagnostic interpretation) of the abnormalities on the X-ray or electrocardiogram. By making subjects request additional information, which was verbal rather than visual, we tried to force them to use analytic information processing as these requests should have been made on the basis of analysis and interpretation of prior information.

Five cases were created for each clinical presentation. The provided information was identical for each of the five cases. In one of the five cases the requested information was consistent with an initial diagnostic hypothesis. In the four other cases the requested information was consistent with an alternative diagnosis that was the correct diagnosis for this case. The alternative diagnoses varied in the frequency with which they are encountered in clinical practice, and their clinical urgency, relative to the initial diagnostic hypotheses. Two practicing internists and one resident (RH, MA and LH, respectively) agreed on the frequency and urgency of the alternative diagnoses – relative to the initial diagnostic hypotheses – beforehand. The five different case types are shown in Figure 1. Figure 2 shows the diagnoses for the clinical presentation of chest pain. The correct diagnosis for each case was agreed upon by same internists and resident. We scored a correct diagnosis as 1 and an incorrect diagnosis as 0.

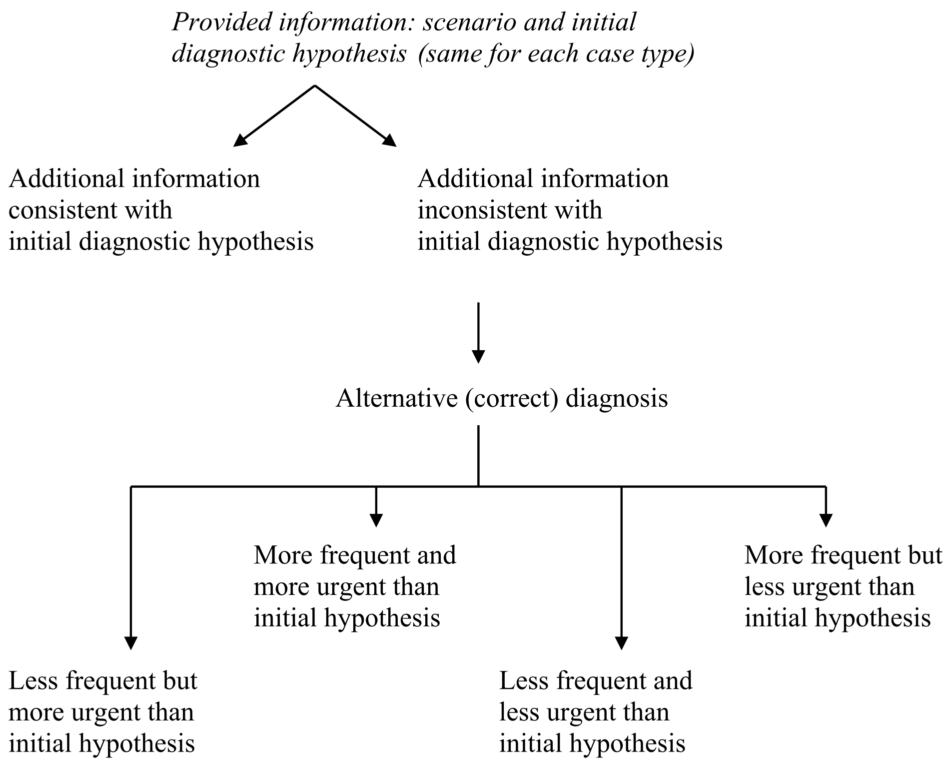

Figure 1. Format of the cases created for each clinical presentation

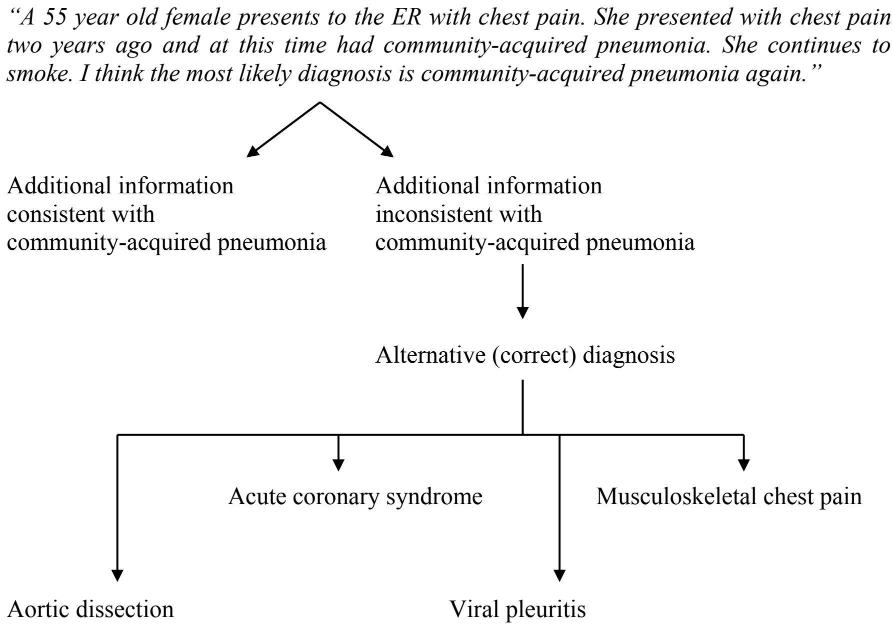

Figure 2. Case format for the clinical presentation of chest pain

Using computer-generated random numbers we randomized subject to receive three of five different case types, one for each of the clinical presentations included in the study. We concealed the cases until the resident has selected a study ID number and they were then given the cases corresponding to the ID number. This process allowed us to manipulate three variables that we wished to study: an initial diagnostic hypothesis, correct versus incorrect; and the effect of both clinical frequency and clinical urgency of an alternative diagnosis on diagnosis selection.

Statistical analyses

We had planned to use multiple logistic regression to study the effect of an initial diagnostic hypothesis, frequency and urgency on diagnosis selection and diagnostic performance. We found, however, that a correct initial diagnostic hypothesis was always retained, such that it was not possible to generate an odds ratio for this variable. To evaluate the effect of an initial diagnostic hypothesis on analytic processing, therefore, we used Fisher's exact test to compare the proportions of initial diagnostic hypothesis chosen as the final diagnosis for cases in which this hypothesis was correct and incorrect. We used the same test to compare the diagnostic success rate for cases in which this hypothesis was correct and incorrect. The risk ratio with 95% confidence intervals was used to estimate effect size. To assess the impact of the clinical frequency and urgency of an alternative diagnosis on diagnosis selection, we used the proportion comparison test to evaluate whether the proportion of more frequent, or more urgent, alternative diagnoses selected was different from that expected by chance alone. Statistical analyses were performed using STATA version 8.0.

RESULTS

All 19 invited residents participated in the study and provided a diagnosis for the three cases within the 12 minutes allowed for the OSCE station. In 11 of the 57 cases an initial diagnostic hypothesis was the correct diagnosis. For the 46 cases in which the alternative diagnosis was correct this diagnosis was more frequent than an initial diagnostic hypothesis in 25 cases and more urgent in 22 cases.

The effect of an initial diagnostic hypothesis on analytic information processing

Selection of an initial diagnostic hypothesis as the final diagnosis and diagnostic performance did not vary between the three clinical presentations. When an initial diagnostic hypothesis was correct this was chosen as the final diagnosis in all cases compared to 10.9% of cases in which an initial diagnostic hypothesis was incorrect (risk ratio 9.2 [4.0, 21.1], $p < 0.001$). Diagnostic success rate was higher when an initial diagnostic hypothesis was correct compared to cases in which an initial diagnostic hypothesis was incorrect (100% vs. 65.2%, risk ratio 1.5 [1.2, 1.9], $p = 0.02$).

The effect of clinical frequency and urgency on analytic information processing

In 41 cases an initial diagnostic hypothesis was rejected. In 24 cases subjects selected a diagnosis encountered more frequently in clinical practice than the rejected initial diagnostic hypothesis, a proportion that did not differ from that expected by chance alone (58% [42, 74], $p = 0.3$). In 20 cases subjects selected a more urgent alternative diagnosis and this proportion, also, did not differ from that expected by chance alone (49% [33, 65], $p = 0.9$).

DISCUSSION

The effect of an initial diagnostic hypothesis on analytic information processing

We found that when an initial diagnostic hypothesis was correct it was retained in all cases. If, however, the hypothesis was incorrect then it was rejected in almost 90% of cases. This rejection rate was higher than that observed in studies in visual domains, although these studies also noted that an initial hypothesis was rejected more frequently when the diagnosis was incorrect.[11;12] The higher rejection rate of an incorrect initial hypotheses in the present study may be due to our subjects having greater clinical experience than those in other studies. Despite most incorrect diagnostic hypotheses being rejected, there was poorer diagnostic performance when an initial hypothesis was incorrect, consistent with the results of studies on automatic processing of visual information.[11;12] We interpreted these results as an initial diagnostic hypothesis biasing analytic information processing – suggesting that, similar to automatic processing of visual information, analytic processing of non-visual information also involves processing with an initial diagnostic hypothesis in mind.

Faulty information processing contributes to most adverse clinical events, previously referred to as "medical error".[22] Our results suggest that even if an initial diagnostic hypothesis is tested with analytic information processing an incorrect hypothesis impairs diagnostic performance. It has been suggested that generating an initial diagnostic hypothesis is so ingrained into medical diagnosing, as it is in every day life, that it may not be possible to prevent this from occurring,[19;20] and attempting to do so may actually reduce diagnostic performance.[21] As such, preventing an initial diagnostic hypothesis generation is unlikely to be possible or helpful. Both experts and novices generate initial hypotheses, but experts are more likely to generate a hypothesis that is correct.[23] Strategies designed to increase the likelihood of an initial diagnostic hypothesis being correct may, therefore, have a role in reducing adverse clinical events.

The effect of clinical frequency and urgency on analytic information processing

We chose to study the effects of clinical frequency and urgency on information processing as indicators of bias due to previous clinical experience, i.e., processing with previously encountered diagnoses in mind. We found that selection of a diagnosis was not influenced by either clinical frequency or urgency and interpreted this finding as suggesting that, in a situation where an initial hypothesis is rejected, analytic processing in search of an alternative diagnosis is data-driven – i.e., the same data used to reject an initial hypothesis are used to find an alternative hypothesis.

Study limitations

This study has some limitations. We suggested an initial diagnostic hypothesis rather than allowing subject to generate their own hypotheses. Previous work has, however, found that the impact of a suggested hypothesis on information processing is similar to that of a self-generated hypothesis and this would appear, therefore, to be a valid substitute.[24] Substituting a suggested hypothesis for a self-generated hypothesis also has face validity with clinical practice, particularly for consultants at teaching hospitals, where cases are typically reviewed with a clerk or resident who has gathered the data and presents the clinical scenario with their diagnostic hypothesis.

Rather than control recent clinical experience by, for example, a uniform training period of practice cases, we used the experience of practicing general internists and a resident to represent the likely clinical experience of our subjects.[6] Our justification for this is that we felt it unlikely that a brief training period of simulated cases would replace the effect of several years of real-life cases.

Conclusion

In this study we found that, similar to automated processing in visual domains, an initial diagnostic hypothesis appears to bias analytic information processing in non-visual domains. This would suggest that analytic processing is diagnosis-driven, at least initially. When an initial diagnostic hypothesis is rejected it would appear that the same data used to reject this diagnosis are used to find an alternative diagnosis. Given the association between information processing and adverse clinical events, we feel that further studies are needed to evaluate ways of improving diagnostic performance. These include strategies to increase the likelihood of an initial hypothesis being correct and/or strategies aimed at reducing the bias of an initial hypothesis on analytic information processing.

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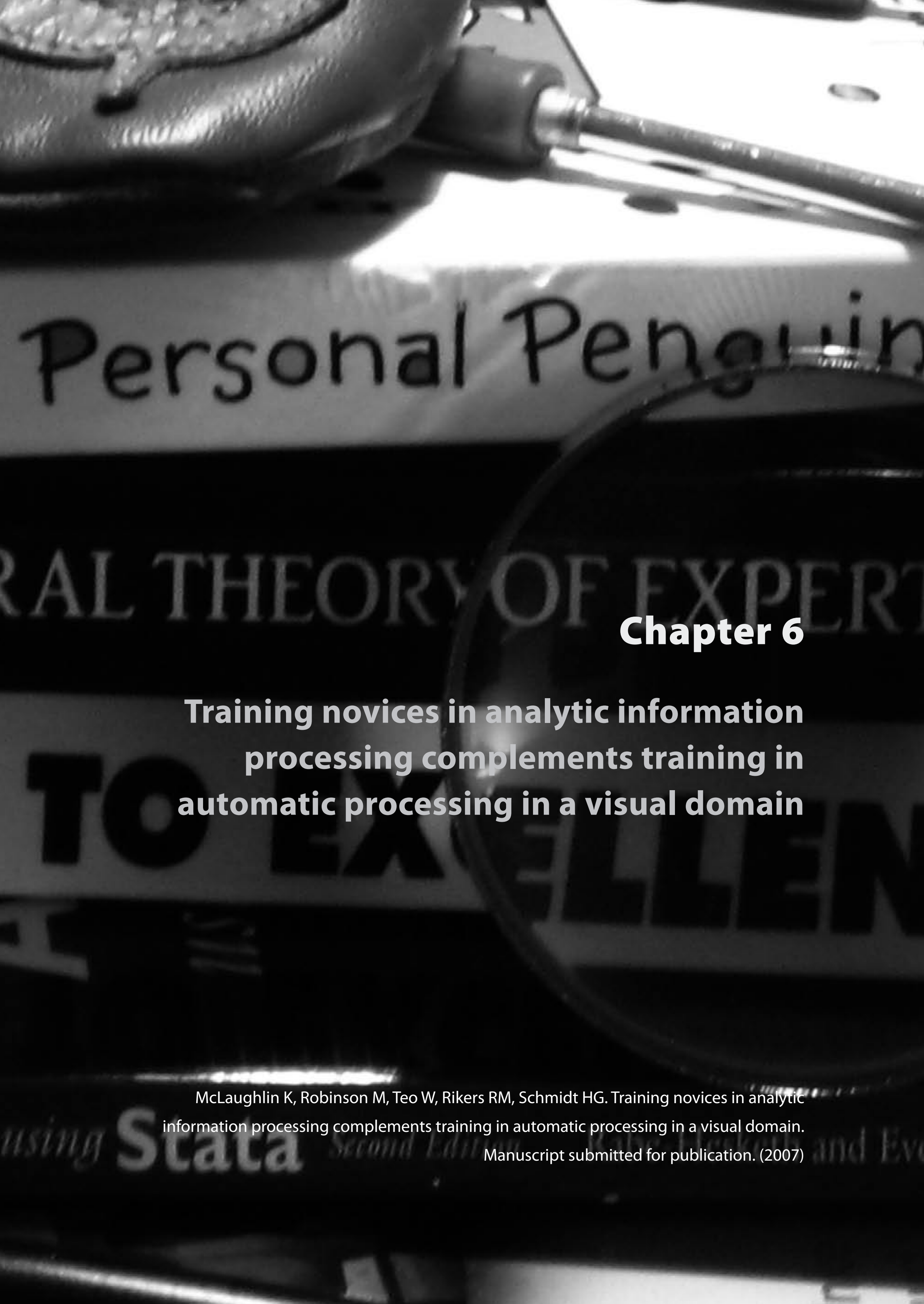

Chapter 6

Training novices in analytic information processing complements training in automatic processing in a visual domain

McLaughlin K, Robinson M, Teo W, Rikers RM, Schmidt HG. Training novices in analytic information processing complements training in automatic processing in a visual domain. Manuscript submitted for publication. (2007)

ABSTRACT

Background. There is disagreement on the contribution of analytic information processing to diagnostic performance in visual domains. Our objective was to study the effects of training in analytic processing on diagnostic performance of medical students in a visual domain. In view of the impact that prior training may have on this effect we chose to study a non-medical visual domain: wildlife identification.

Methods. First year medical students were randomly assigned to one of three groups for training in wildlife identification: Group A, automatic processing; Group B, analytic processing with blinding of visual information; and group C, reduced training in automatic processing combined with analytic processing. Multiple linear regression was used to study the effect of training on diagnostic performance after adjustment for species.

Results. Group B had reduced diagnostic success (82.1 % vs. 89.3% for Group A and 89.3% for Group C, $d = 0.69$, $p = 0.018$). Despite receiving one third of the training in automatic processing, Group C had similar diagnostic performance to Group A.

Conclusion. Training in automatic processing appears to enhance the effects of training in analytic processing and vice versa, suggesting that training in both processing strategies is complementary. In medical education, training in automatic processing is provided by clinical experience – which is a scarce resource. Further studies are needed to evaluate whether training in analytic processing can enhance the efficiency of clinical training in medicine.

Information processing when making a medical diagnosis

Diagnosing is frequently an effortless task – particularly for experienced physicians solving routine problems[1] – involving connecting clinical and/or biomedical information of a case to knowledge stored in long term memory. If needed, *automatic* processing may be supplemented by *analytic* information processing, requiring greater effort and conscious analysis, synthesis and interpretation of clinical and/or biomedical information.[2]

Observational studies have found that information processing varies between medical domains – automatic processing of clinical information predominates in visual domains and analytic processing of biomedical information is used more frequently when interpretation of laboratory information are involved.[3-5] Processing may be affected by the experimental conditions; analytic processing of biomedical information is increased by presenting the results of investigations without a clinical context.[5-8] Clinical experience may also influence information processing, although opinions differ on whether experienced physicians use more or less analytic information processing.[8-12]

The contribution of analytic information processing to diagnostic performance in different domains

In non-visual domains requiring processing of laboratory information, we, and others, have found a positive association between analytic processing of relevant biomedical information and diagnostic performance (Chapters 3 and 4 of this thesis).[5] In visual domains, however, the contribution of analytic processing to diagnostic performance is less certain. When clinical information is provided automatic processing dominates analytic processing on visual tasks and diagnoses are frequently made on the basis of superficial features of a case.[7;13]

The effect of training in analytic processing on visual tasks appears to be conditional upon the experience of the learner – analytic processing is a more successful training strategy in residents[14] and automatic processing is more successful in students or extreme novices.[15;16] Ark and colleagues found that training in both automatic and analytic processing resulted in a better diagnostic performance then training in either strategy alone.[17] Kulatunga-Moruzi, *et al.* found, however, that diagnostic performance of practicing physicians could be either reduced or enhanced depending upon the type of information used to facilitate analytic processing.[18]

Given the inconclusive results of prior studies, we chose to evaluate further the contribution of analytic processing to diagnostic performance in a visual domain. Respecting the potential bias due to previous experience we chose to observe the effect of training on novices. As our subjects had completed one third of their undergraduate medical training – including training in visual domains such as dermatology, electrocardiogram and chest

X-ray interpretation – we felt that they were no longer novices in visual domains in medicine. We, therefore, tested out study hypothesis in a non-medical visual domain, wildlife identification, and included only subjects without previous training in this domain. We considered four possible effects of training in analytic processing to diagnostic performance: *critical*, in which case training in analytic processing should be associated with enhanced performance; *detrimental*, in which case training in analytic processing should be associated with reduced performance; *redundant*, in which case training in analytic processing should not be associated with performance (performance should depend upon the amount of training in automatic processing); and *complementary*, in which case training in analytic processing should enhance the effect of training in automatic processing, and vice versa.

METHODS

Study sample and design

The Conjoint Research Ethics Board at the University of Calgary granted ethical approval for this randomized controlled trial. Subjects were 41 first year medical students at the University of Calgary. The University of Calgary has a three years undergraduate curriculum and the students in this study were at the end of their first year. We invited all students (n = 100) to participate and obtained informed consent prior to randomly allocating subjects to one of three training groups. At the time of recruitment we specified that we were interested in studying only students without prior training in wildlife identification and that students with previous training in this area should not participate. The content areas were two groups of wildlife; ungulates and birds of prey, and within each group there were five examples. The five ungulates were: moose, elk, woodland caribou, mule deer, and white-tailed deer. The five birds of prey were: bald eagle, golden eagle, osprey, hawk, and falcon.

Training conditions

The three training groups were: *automatic* processing alone (Group A); analytic processing alone with *blinding* from visual information (Group B); and *combined* automatic and analytic processing (Group C). We gave Group C the same training in analytic processing as Group B combined with one third of the training in automatic processing of Group A. The training period for each group was 30 minutes. During the training period we showed Group A subjects 30 photographs, three for each animal, for one minute each. The name of the animal appeared at the top of the photograph and there was no verbal communication between subjects and trainer. We trained Group B subjects on the use of two diagnostic schemes (15 minutes for each scheme) for identifying animals within each group, based upon the approach recommended in popular wildlife texts.[19;20] The scheme for ungulates is shown in Appendix 5. We did not show this group photographs during the training session. We taught them the characteristic features of each animal (e.g., an elk is approximately 4½ foot tall and has a large white rump patch) and the features used to discriminate between animals (e.g., if the ungulate is 3 foot tall then the presence of a white neck indicates woodland caribou). We gave Group C subjects the same training on the use of diagnostic schemes but did so while showing them photographs of the appropriate animals. We showed Group C subjects one photograph per animal, corresponding to the first of three photographs shown to Group A subjects.

Evaluation of diagnostic performance

We gave the three groups a short-answer evaluation immediately after training session, comprising 20 new photographs, two for each animal, and asked subjects to identify the animal in each photograph. We showed each photograph for 45 seconds. We allowed Groups B and C subjects to refer to the diagnostic schemes during the evaluation.

Statistical analyses

We used multiple linear regression to compare diagnostic performance for the three training groups. Species (ungulates vs. birds of prey) and interaction between species and training group were also considered in the regression model. We used STATA version 8.0 for our statistical analyses.

RESULTS

Of the 41 subjects who participated in the study, 15 were randomized to Group A, 12 to Group B and 14 Group C. There was no interaction between species and training group (p = 0.3) and no association between species and diagnostic performance (p = 0.9). The diagnostic success rates (±SD) for the three groups were 89.3% (±9.0), 82.1% (±10.8) and 89.3% (±9.8), respectively (Figure). The diagnostic success rate was significantly lower for subjects who had received training in analytic processing alone (Group B, regression coefficient -7.2 [-13.2, -1.3], p = 0.018). The effect size for this difference was ‘medium to large’ (d = 0.69).

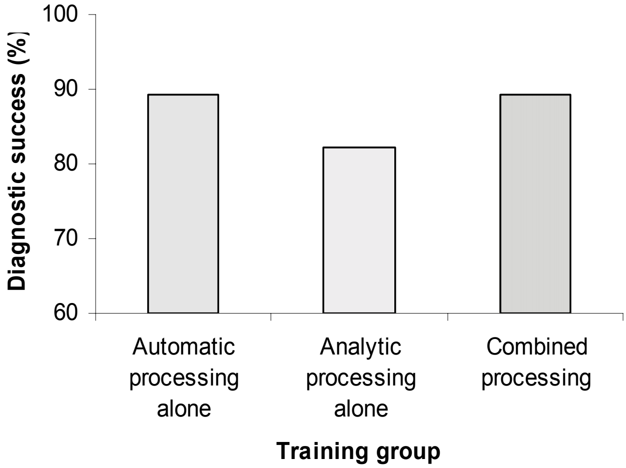

Figure. The effect of training in automatic processing, analytic processing or both on diagnostic performance

DISCUSSION

The effect of training in analytic information processing on diagnostic performance

We considered four possible effects of training in analytic processing to diagnostic performance: *critical*; *detrimental*; *redundant*; and *complementary*. The lower success rate in Group B is evidence against training in analytic processing being *critical* to diagnostic performance. The lack of difference in performance between Groups A and C is evidence against training in analytic processing being *detrimental*. The observation that Group C had similar diagnostic performance to Group A, despite receiving one third of the amount of training in automatic processing, is evidence against training in analytic processing being *redundant*. The observations that training in automatic processing enhanced the effect of training in analytic processing (Group C outperformed Group B) and training in analytic processing enhanced training in automatic processing (the performances of Groups A and C were equal despite the former receiving less training in automatic processing) are consistent with training in both processing strategies being *complementary*.

In our combined training group we limited automatic processing training to viewing one picture of each animal. This allowed us to ensure that the training times were equal for each group and that Groups B and C received an equal amount of training in analytic processing; practicing analytic processing on additional photographs would have increased the amount of training in analytic processing. Consequently, our results should not be interpreted as more training simply being better than less training as the combined group performed better with the same amount of analytic training and equally well despite less automatic training.

Mechanisms of the interaction between information processing strategies

In their recent study, Ark and colleagues found that diagnostic performance is reduced when novice learners try to solve a problem using analytic processing alone.[17] This confirms the result of a previous study and is also consistent with the reduced performance of Group B in our study.[16] Problem solving without an initial diagnostic hypothesis – generated through automatic processing – leads to increased analysis and interpretation of features that are either irrelevant or absent.[17] It is likely, therefore, that automatic processing helps to focus analytic processing on relevant information.

Studies in which analytic processing follows automatic processing suggest that analytic processing may enhance automatic processing by reducing the bias of the initial diagnostic hypothesis generated by automatic processing.[17] This explanation may, however, be incomplete. It has also been shown that diagnostic performance of practicing physicians may be affected when analytic processing precedes automatic processing.[18] The nature of this interaction depends upon the type of information processed – a comprehensive list of features both for and against the correct diagnosis reduces performance, while a shorter list of features consistent with the correct diagnosis enhances performance.[18] As it has been shown previously that automatic processing may focus on irrelevant features of a case – such as a patient's occupation – analytic processing may complement automatic processing by focusing this on relevant, rather than irrelevant, information.[7]

Study limitations

Our study has some limitations, including the fact that the subject area was non-medical. We specifically chose this domain, however, to avoid the potential bias of previous training – our subjects had received training in analytic information processing in the visual domains of medicine that are typically studied. Nonetheless, we need to repeat this study in medical domains before making recommendations on training in medical education.

We did not evaluate our subjects' abilities to identify wildlife prior to training. We did, however, specify that we wished to study only subject without prior training in wildlife identification and, by randomly allocating subjects to different training groups, we reduced the potential for allocation bias due to differences in abilities between groups. Anticipating a small sample size (subjects were not rewarded for participation in this study), we did not include a control group as this would have reduced the power of our study. Without a control group we cannot show that training improved diagnostic performance; it is possible that training actually impaired performance. But, given the high diagnostic success rates in all training groups (> 80%), and the fact that subjects had no previous training in this domain, we think it unlikely that training impaired performance.

The results of this study may be highly dependent on the content area and group of learners. For example, the content area studied is visual and the results may not be relevant to tasks that are non-visual, such as diagnosing electrolyte problems. Similarly, the effect of training in one group of learners, e.g., novices, is not generalizable to groups of learners with greater experience or expertise.[14;16;21]

Conclusion

In our study we found that in a non-medical visual domain, the effects on diagnostic performance of training novices in analytic and automatic processing were complementary. In medicine, training in automatic processing is provided by clinical experience and there appears to be no substitute for this. If the results of our study are confirmed in medical domains, this would suggest that training in analytic information processing may enhance the efficiency of training in automatic processing; similar diagnostic performance may be achievable with less clinical experience. Due to an increase in the size of medical school classes, and a reduction in the number of hours residents are permitted to work, physicians of the future may have less clinical experience at the end of their training than did their predecessors. Identifying ways of training physicians such that reduced clinical experience does not equate to reduce diagnostic performance may, therefore, be important.

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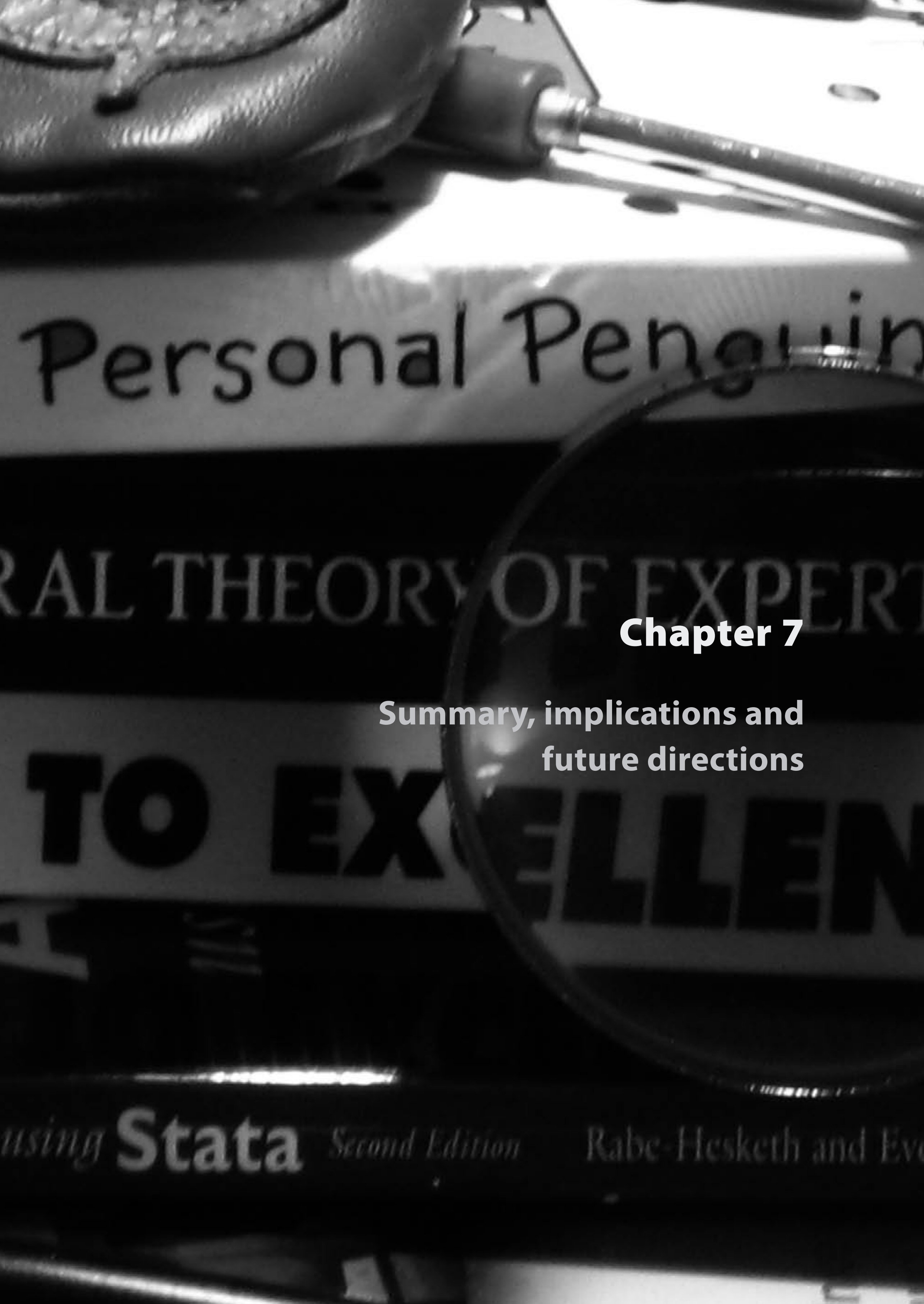

Chapter 7

Summary, implications and future directions

Finding the recipe for medical expertise

In every profession there are a few individuals that consistently demonstrate superior performance and many who try to emulate this. In medicine, superior diagnostic performance is one of the defining features of expertise. Making a diagnosis is a complex cognitive task, involving processing of new information and stored knowledge. As each case presents unique information and each physician's knowledge differs from that of his colleagues, information processing is both case-specific and physician-specific. Yet, despite these specificities, researchers in medical education must find generalities in information processing. Such generalities are used to describe the paradigm of information processing and may identify ingredients of the expertise recipe that can, and should, be taught.

The current paradigm of information processing assumes diagnosticians create mental representations of problems – containing varying degrees of clinical and biomedical information – that are used to retrieve and apply stored clinical and biomedical knowledge.[1] With increasing clinical experience lower level, biomedical concepts become encapsulated within a smaller number of higher level, clinical concepts: the mental representations of experts are less elaborate than those of intermediates and are dominated by clinical information.[2;3] Information processing may be *automatic* (unconscious processing of information and diagnosing on the grounds of similarity to a previous case), *analytic* (conscious processing of information and explaining the diagnosis using the information contained within the case), or a combination of both. With increasing clinical experience diagnosticians rely more on automatic processing, particularly when solving routine problems within their area of expertise.[4;5]

If experts prefer automatic processing of clinical information, does analytic processing, including processing of biomedical information, contribute to diagnostic performance? Studies addressing this question are described in detail in Chapter 1 and are reviewed briefly below.

Previous studies addressing analytic processing and diagnostic performance

Patel *et al.* found that medical students applied biomedical knowledge inconsistently or incorrectly when explaining their diagnosis of a case of endocarditis. They concluded that clinical and biomedical knowledge exist as distinct entities, where processing of clinical information is used to make a diagnosis and analytic processing of biomedical information is used to provide a pathophysiological explanation.[6] In this case the contribution of analytic processing of biomedical information to diagnostic performance could be described as *redundant*.

Lesgold *et al.* found that correct interpretation of abnormal chest X-rays involved the explicit use of anatomical and pathophysiological knowledge and that expert radiologists applied more of this type of knowledge than either junior or senior residents.[7] Gilhooly *et al.* found that registrars had more detailed case recall and used more clinical and biomedical information than house officers and medical students to diagnose and explain abnormal electrocardiograms.[8] Based on these results analytic processing could be described as *critical* to diagnostic performance.

Kulatunga-Moruzi *et al.* found that facilitating analytic information processing using a comprehensive list of clinical features reduced the performance of dermatologists and family medicine specialists when diagnosing dermatology photographs, in which case analytic processing could be described as *detrimental* to diagnostic performance. [9]

Boshuizen and Schmidt found that experienced physicians used fewer biomedical propositions when diagnosing, but more when explaining their diagnosis for a case of acute pancreatitis – suggesting that biomedical knowledge is encapsulated within clinical knowledge and applied tacitly during information processing.[10] Verkoeijen *et al.* found that experienced physicians use more analytic information processing in the absence of clinical context, suggesting that they can unfold encapsulated knowledge and apply this analytically if needed.[11] Based upon these studies the contribution of analytic processing of biomedical information to diagnostic performance could be described as *optional*.

Based upon the existing literature a range of contradictory adjectives could be used to describe the contribution of analytic information processing to diagnostic performance. In this thesis we tried to identify the most appropriate adjective(s) by using a combination of study designs and techniques to assess information processing of different groups of learners in different domains.

Summary of the findings of this thesis

Is analytic processing of relevant biomedical concepts associated with diagnostic performance when solving acid-base and electrolyte problems?

Our starting point was to question whether analytic processing of biomedical information had any association with diagnostic performance. In Chapter 2 we used think aloud to assess information processing in an observational study designed to be sensitive to this association: we chose a non-visual domain in which subjects were given lab data – electrolyte and acid-base problems – and considered analysis of even one relevant biomedical concept, chosen *a priori*, to represent analytic processing of relevant biomedical concepts. We studied nephrologists and first-year medical students – assuming the former had both clinical experience and biomedical knowledge, while the latter had biomedical knowledge but minimal clinical experience – to assess whether the association varied with clinical experience. We predicted that if analytic processing of relevant biomedical concepts is helpful when diagnosing electrolyte and acid-base problems then it should be used frequently and have a positive association with diagnostic performance. Alternatively, if analytic processing of relevant biomedical concepts is unhelpful then it should be used infrequently and have either no association or a negative association with diagnostic performance.

Nephrologists and students used analytic processing of relevant biomedical concepts in more than 80% of electrolyte and acid-base problems. We attributed this high proportion to these problems being relatively infrequent and challenging, such that it may be difficult to solve them without conscious application of stored biomedical knowledge. Students solving these problems without analytic processing of relevant biomedical concepts had reduced performance – likely due to deficient biomedical knowledge. In nephrologists this association was attenuated, either due to encapsulation of biomedical knowledge into clinical knowledge or clinical knowledge compensating for the lack of biomedical knowledge.

From this study we concluded that analytic processing of relevant biomedical concepts is associated with diagnostic performance and that clinical experience modifies this association. But we were unable to describe how much analytic processing of relevant biomedical concepts contributes to diagnostic performance.

What is the contribution of analytic processing of relevant biomedical concepts to diagnostic performance when solving electrolyte and acid-base problems?

In Chapter 3 we addressed this question by reanalyzing the think aloud transcripts from the study in Chapter 2. But this time we treated processing as an interval rather than a dichotomous variable. We considered the four possible contributions and predicted the findings based upon each of these descriptions. If *redundant*, there should be no association with performance; if *critical*, performance should be positively associated with, and dependent upon, analytic processing of relevant biomedical concepts; if *detrimental*, there should be a negative association with performance; and if *optional*, performance should be positively associated with, but not dependent upon, analytic processing of relevant biomedical concepts.

In both students and nephrologists the number of relevant biomedical concepts processed was positively associated with performance on electrolyte and acid-base problems. In students the number of concepts processed was a good predictor of performance – suggesting that analytic processing of relevant biomedical concepts is *critical* in the absence of clinical experience. But the number of concepts processed was a poor predictor of performance in nephrologists, suggesting that analytic processing of relevant biomedical concepts is *optional* in experienced physicians.

From this study we concluded that the contribution of analytic processing of relevant biomedical concepts to diagnostic performance is reduced in experienced physicians compared to students – consistent with knowledge encapsulation as a result of clinical experience. But so far we had considered only biomedical information; what about clinical information? Also, we did not know to what extent these findings were specific to the domain studied or the technique used to study information processing.

What is the contribution of biomedical information processing relative to clinical information processing when making a hematological diagnosis?

To answer this question in Chapter 4 we observed information processing of clerks and residents solving hematology problems. We used preference elicitation to ascribe utilities to information bundles – allowing us to compare relative utilities in addition to quantifying the use of biomedical and clinical information. We predicted that if biomedical information is of secondary importance when diagnosing then biomedical information should be processed later than clinical information and should not contribute to diagnostic performance. We considered the same four possible contributions to performance as the previous study: *redundant, critical, detrimental,* and *optional*.

Subjects were as likely to ascribe the highest utility to biomedical as clinical information – suggesting that the practice of sequentially processing clinical then biomedical information is a function of experimental conditions or medical tradition. Biomedical information processing was positively associated with, but a poor predictor of, diagnostic performance. This suggests that for clerks and residents solving hematology problems the contribution of biomedical information processing is optional – helpful, but not critical – likely due to the concomitant contribution of clinical information processing to diagnostic performance.

From this study we concluded that analytic processing of biomedical information contributes to diagnostic performance in domains other than electrolytes and acid base problems and can be assessed by techniques other than think aloud. But so far we had considered only analytic processing; what about automatic processing? Are automatic and analytic processing independent?

Does an initial diagnostic hypothesis bias analytic information processing in non-visual domains?

In Chapter 5 we sought to answer this question by manipulating the initial diagnostic hypothesis – a product of automatic information processing – to evaluate its effect on analytic processing and performance of residents diagnosing patients with dyspnea, headache and chest pain. We predicted that if an initial hypothesis biases analytic processing then an incorrect hypothesis should reduce diagnostic performance. Alternatively, if analytic processing is objective and data-driven then diagnostic performance should be unaffected. We also predicted that if, in a case where an initial hypothesis is rejected, selection of an alternative diagnosis is influenced by previously encountered diagnoses then the diagnosis selected should be encountered more frequently, or have greater clinical urgency, than the rejected hypothesis. Alternatively, if the search for an alternative diagnosis is objective and data-driven then this should be unaffected by frequency or urgency.

Diagnostic success rate was higher for cases where the initial hypothesis was correct, consistent with an initial hypothesis biasing analytic processing. Clinical frequency and urgency were not associated with alternative diagnosis selection, suggesting that alternative hypothesis selection is driven by data used to reject an initial hypothesis.

From this study we concluded that analytic processing occurs with an initial diagnostic hypothesis in mind, implying that the effect of analytic processing on diagnostic performance is conditional upon the result of automatic processing. But here we manipulated only automatic processing. Ideally, to study the interaction between automatic and analytic processing both variables should be manipulated.

Does training in analytic information processing improve diagnostic performance in a visual domain?

To answer this in Chapter 6 we randomly assigned first year medical students to one of three groups for training in wildlife identification: automatic processing alone; analytic processing alone; and combined automatic and analytic processing. We chose wildlife identification as our subjects had received previous training in analytic information processing the visual domains of medicine. We excluded subject with prior training in wildlife identification in order to study the effect of training in novices. We considered four possible effects of training in analytic processing to diagnostic performance: *critical*, in which case training in analytic processing should be associated with enhanced performance; *detrimental*, in which case training in analytic processing should be associated with reduced performance; *redundant*, in which case training in analytic processing should not be associated with performance (performance should depend upon the amount of training in automatic processing); and *complementary*, in which case training in analytic processing should enhance the effect of training in automatic processing, and vice versa.

Training in analytic processing alone was associated with poorer diagnostic performance, suggesting that training in analytic processing is not critical and cannot replace training in automatic processing. But combining the same amount of training in analytic processing with training in automatic processing improved performance – automatic processing enhanced analytic processing. Also, combined training had a similar effect to three times the amount of training in automatic processing – analytic processing enhanced automatic processing. These results are consistent with training in automatic processing and analytic processing being complementary.

Considering our five studies as a whole, the most appropriate adjective to describe the contribution of analytic information processing to diagnostic performance is dependent upon study design and clinical experience. When studied in isolation, analytic processing of biomedical information appears to be *critical* in the absence of clinical experience but *optional* in the presence of clinical experience. When studied alongside automatic processing, the contribution of analytic processing is *conditional* upon automatic processing. Finally, with regards to improving diagnostic performance through training, the effects of training in automatic and analytic processing are *complementary*.

Implications of the results of this thesis

The results of our observational studies suggest that performance is improved when relevant biomedical concepts are applied when diagnosing. To learners hoping to improve their performance on electrolyte or hematology problems we can say that analytic processing of relevant biomedical concepts is associated with enhanced performance – suggesting that increasing their understanding and use of these concepts may improve performance. The message to educators is to identify the relevant concepts for each clinical presentation – concepts that, if applied, are associated with enhanced performance – and improve understanding of these concepts so that learners have the option of applying them when diagnosing.

But analytic processing of biomedical information is not a panacea. No single type of information or processing will solve all problems. The results of our intervention studies suggest that, while analytic processing may compensate for erroneous automatic processing, diagnostic performance is at its best when analytic processing complements accurate automatic processing. To enhance their diagnostic performance, therefore, learners should improve their understanding, and use, of both types of information and processing. The message to medical educators is to create holistic learning experiences. Biomedical and clinical information are complementary[12], as are automatic and analytic processing[13] – so teach the yin with the yang.

Future studies

Building upon our current studies we intend to explore further differences in *information* and *processing* related to medical expertise. Using a combination of concept sorting to study concepts in static knowledge[14] and preference elicitation to study concepts applied when diagnosing, we hope to identify relevant clinical and biomedical concepts for different clinical presentations. In intervention studies we will then study the effects of using these concepts on diagnostic performance.

Thus far most of the work on medical expertise has focused on its acquisition. Equally important is evaluating ways of preventing the age-related decline in performance.[15] We aim to study information processing by physicians towards the end of their career to identify variables associated with poor diagnostic performance in this group. It is likely that the reasons for poor performance and, consequently, the educational needs are quite different at this end of the spectrum.

At the present time opinion-based review articles and books on creating medical expertise dominate the literature, including how to change curricula to mass-produce expertise. Opinions fill the evidence void. Evidence-based medical education is on the horizon, but we are a long way from making evidence-based recommendations on creating and maintaining medical expertise. As researchers in medical education we have not yet found the recipe for medical expertise – but we are gradually finding ways to find it.

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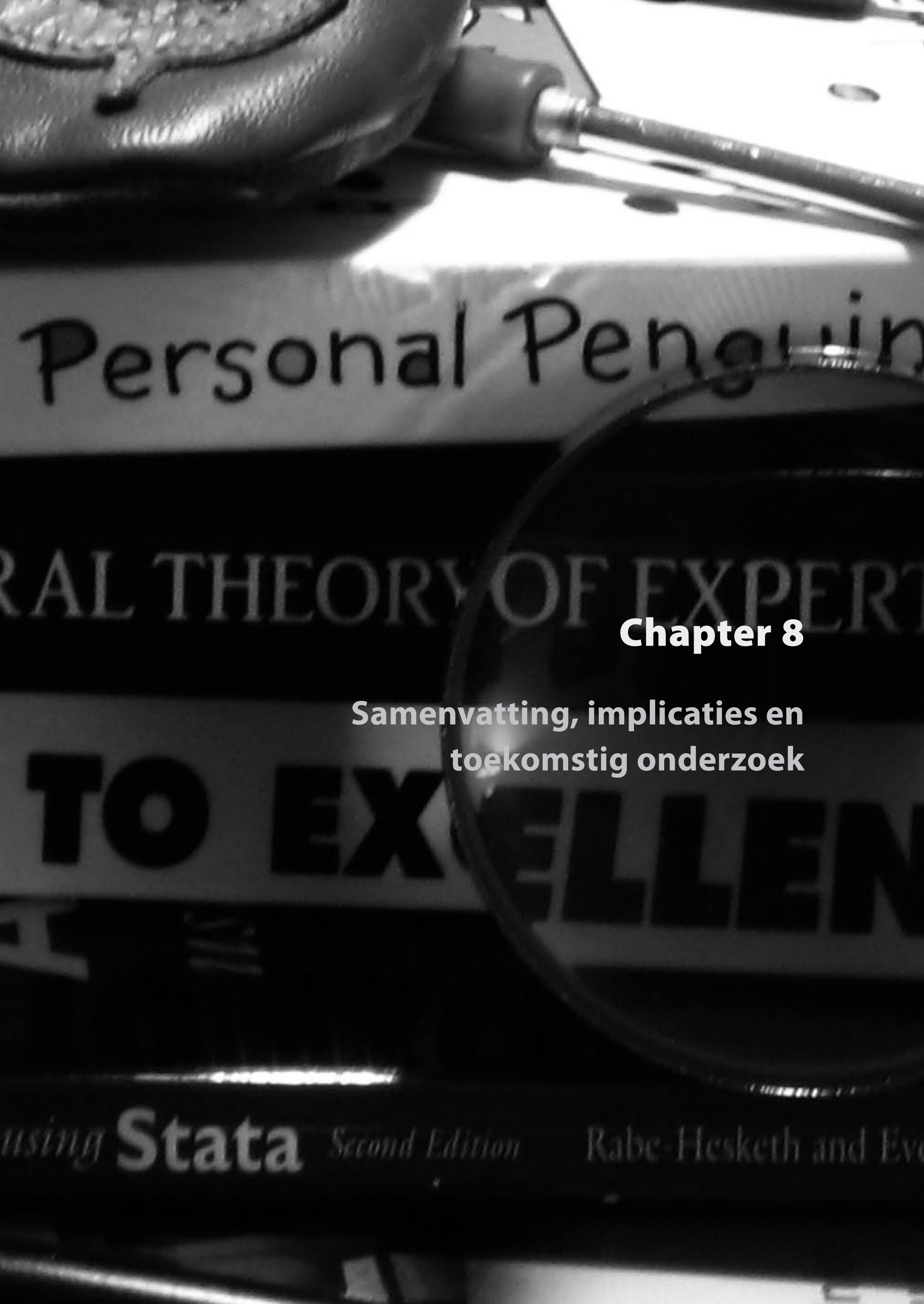

Chapter 8

Samenvatting, implicaties en toekomstig onderzoek

OP ZOEK NAAR EEN RECEPT VOOR MEDISCHE EXPERTISE

In elk beroep is er een aantal mensen dat voortdurend hoge prestaties levert en velen die dat trachten te evenaren. In de medische wereld behoren superieure diagnostische prestaties tot de kenmerken waaraan je expertise kunt afmeten. Een diagnose stellen is een complexe cognitieve taak die bestaat uit het verwerken van nieuwe informatie en opgeslagen kennis. Omdat elke casus unieke informatie oplevert en de kennis van elke arts verschilt van die van zijn collega's, is informatieverwerking zowel casusafhankelijk als artsafhankelijk. Desondanks moeten onderzoekers op het gebied van medisch onderwijs toch zoeken naar generalisaties in de informatieverwerking. Dergelijke generalisaties worden gebruikt om het paradigma van informatieverwerking te omschrijven, en eventueel ingrediënten te vinden voor van het recept voor expertise dat kan, en zou moeten, worden onderwezen.

Het huidige paradigma van informatieverwerking is dat diagnostici mentale weergaven van een probleem creëren (die klinische en biomedische informatie van verschillende gradaties bevatten), die worden gebruikt om klinische en biomedische kennis op te diepen en toe te passen.[1] Naarmate men meer klinische ervaring krijgt, worden lagere-orde biomedische concepten opgenomen in een kleiner aantal hogere-orde klinische concepten, we noemen dit 'encapsulatie' of inkapseling. De mentale weergaven van experts zijn minder uitgebreid dan die van studenten of minder ervaren artsen, en worden gedomineerd door klinische informatie.[2;3] Informatieverwerking kan automatisch plaatsvinden: onbewuste informatieverwerking en diagnosticering op grond van overeenkomsten met voorgaande casussen; of analytisch: bewuste verwerking van informatie en het verklaren van de diagnose aan de hand van informatie van de casus zelf; of een combinatie van beide. Naarmate diagnostici meer klinische ervaring hebben, vertrouwen ze meer op automatische verwerking, vooral bij het oplossen van routineproblemen op hun eigen vakgebied.[4;5]

Aangezien experts de voorkeur geven aan automatische verwerking van klinische informatie, zou analytische verwerking (inclusief het verwerken van biomedische informatie) kunnen bijdragen aan diagnostische prestaties. Onderzoek hiernaar wordt uitgebreid beschreven in Hoofdstuk 1, en hieronder kort besproken.

Bestaand onderzoek naar analytische verwerking en diagnostische prestaties

Patel toonde aan dat studenten geneeskunde biomedische kennis inconsequent en onjuist toepassen bij het verklaren van hun diagnose bij een geval van endocarditis*, en concludeerde dat klinische en biomedische kennis gescheiden kennisgebieden zijn, waarbij het verwerken van klinische informatie wordt gebruikt bij het stellen van een diagnose, en het analytisch ver-

* Ontsteking hartkleppen

werken van biomedische informatie wordt gebruikt om een pathosfysiologische verklaring te geven.[6] In dit geval kan de bijdrage van het analytisch verwerken van biomedische informatie bij het stellen van de diagnose worden gekenmerkt als *overbodig*.

Lesgold toonde aan dat het voor de juiste interpretatie van afwijkende röntgenfoto's van de borstkas nodig was om expliciet gebruik te maken van anatomische en pathosfysiologische kennis, en dat ervaren radiologen vaker dit soort kennis toepasten dan beginnende en ervaren arts-assistenten.[7] Gilhooly toonde aan dat ervaren arts-assistenten een gedetailleerdere herinnering hadden van casussen, en meer klinische en biomedische informatie bezaten dan beginnende arts-assistenten en studenten geneeskunde, om afwijkende elektrocardiogrammen te diagnosticeren en te verklaren.[8] Gebaseerd op deze resultaten zou analytische verwerking kunnen worden beschreven als *essentieel* bij het stellen van een diagnose.

Kulatunga-Moruzi toonde aan dat door het bevorderen van analytische informatieverwerking door middel van een uitgebreide lijst met klinische symptomen, de prestatie van dermatologen en huisartsen verslechterde bij het diagnosticeren van dermatologische foto's, waardoor de analytische verwerking beschreven kan worden als *nadelig* bij het stellen van een diagnose. [9]

Boshuizen toonde aan dat ervaren artsen bij een geval van acute pancreatitis[*] minder gebruik maakten van biomedische kennis bij het stellen van een diagnose, maar meer bij het uitleggen van die diagnose - wat erop zou kunnen wijzen dat biomedische kennis is ingekapseld in klinische kennis en onbewust wordt toegepast bij de informatieverwerking.[10] Verkoeijen toonde aan dat ervaren artsen meer analytische informatieverwerking gebruikten bij het ontbreken van een klinische context, wat laat zien dat ze ingekapselde kennis indien nodig kunnen ontsluiten en analytisch toepassen.[11] Gebaseerd op deze onderzoeken kan de bijdrage van analytische verwerking van biomedische informatie bij het stellen van een diagnose worden gezien als *optioneel*.

Uitgaande van de bestaande literatuur kan een groot aantal tegenstrijdige termen worden gebruikt voor de beschrijving van de bijdrage van analytische informatieverwerking tot het stellen van een diagnose. In dit proefschrift hebben we geprobeerd de meest geschikte term te identificeren door middel van een combinatie van onderzoeksopzetten en -methoden om te onderzoeken welke informatieverwerking verschillende groepen lerenden op verschillende gebieden gebruiken.

Samenvatting van de bevindingen van dit proefschrift

Bestaat er een verband tussen analytische verwerking van biomedische informatie en het stellen van een diagnose bij het oplossen zuur-base en elektrolytische problemen?

Ons uitgangspunt was de vraag of analytische verwerking van biomedische informatie enig verband hield met het stellen van een diagnose. We maakten gebruik van on-line "hardop-

[*] Ontsteking van de alvleesklier

denken" om informatieverwerking te onderzoeken, in een observatiestudie die ontworpen was om deze verbanden aan het licht te brengen: we hebben gekozen voor een niet-visueel domein waarbij proefpersonen laboratoriumdata kregen: elektrolytische en zuur-base-problemen. Al bij analyse van slechts één biomedisch sleutelbegrip (a priori gekozen), werd uitgegaan van analytische verwerking van biomedische informatie. Om vast te stellen of het verband varieerde met de klinische ervaring, onderzochten we nefrologen* en eerstejaars geneeskundestudenten (waarbij werd aangenomen dat de eersten zowel klinische ervaring als biomedische kennis bezaten, terwijl de laatsten wel biomedische kennis hadden, maar minimale klinische ervaring). We voorspelden dat als analytische verwerking van biomedische informatie nuttig is bij het diagnosticeren van elektrolytische en zuur-base problemen, het frequent zou moeten worden gebruikt, en er een positief verband zou moeten bestaan met de diagnostische prestatie. Daarentegen, als analytische verwerking van biomedische informatie niet nuttig is, dan zou het niet frequent gebruikt moeten worden, en zou er of geen verband of een negatief verband moeten bestaan met de diagnostische prestatie.

Zowel nefrologen als studenten maakten bij meer dan 80% van de elektrolytische en zuur-base problemen gebruik van analytische verwerking van biomedische informatie. We schrijven dit hoge percentage toe aan het feit dat deze problemen relatief zeldzaam en uitdagend zijn, zodat ze misschien moeilijk zijn op te lossen zonder bewuste toepassing van opgeslagen biomedische kennis. Studenten die deze problemen oplosten zonder analytische verwerking van biomedische informatie presteerden minder goed - waarschijnlijk als gevolg van ontoereikende biomedische kennis. Bij de nefrologen was dit verband minder sterk aanwezig, ofwel vanwege de encapsulatie van biomedische kennis in klinische kennis, ofwel doordat het gebrek aan biomedische kennis werd gecompenseerd met klinische kennis.

De conclusie van het onderzoek was dat analytische verwerking van biomedische informatie gerelateerd is aan het stellen van een diagnose, en dat klinische ervaring die relatie beïnvloedt. We waren echter niet in staat te beschrijven in hoeverre analytische verwerking van biomedische informatie bijdraagt tot het stellen van een diagnose.

Welke bijdrage levert analytische verwerking van biomedische informatie tot het stellen van een diagnose bij het oplossen van elektrolytische en zuur-base problemen?

Om deze vraag te beantwoorden, hebben we de hardopdenkprotocollen van onze eerdere studie opnieuw geanalyseerd, waarbij we de verwerking ditmaal hebben beschouwd als interval- in plaats van als dichotome variabele. We hebben de vier mogelijke bijdragen geanalyseerd en de uitkomsten voorspeld, gebaseerd op de vier beschrijvingen. Bij *overbodig* zou er geen verband kunnen worden aangetoond met de diagnostische prestatie; bij *essentieel* zou de prestatie een positief verband moeten laten zien met, en afhankelijk moeten zijn van, analytische verwerking van biomedische informatie; bij *nadelig* zou er een negatief verband

* nierspecialisten

moeten blijken met de prestatie; en bij *optioneel* zou de prestatie weliswaar een positief verband moeten hebben met, maar niet afhankelijk moeten zijn van, analytische verwerking van biomedische informatie.

Zowel bij de studenten als bij de nefrologen bestond er een positief verband tussen het aantal verwerkte biomedische begrippen en de diagnostische prestatie bij het oplossen van elektrolytische en zuur-base problemen. Bij de studenten was het aantal verwerkte begrippen een goede voorspeller van de prestatie - wat aantoont dat analytische verwerking van biomedische informatie *essentieel* is bij het ontbreken van klinische ervaring. Bij de nefrologen echter was het aantal verwerkte begrippen een slechte voorspeller voor de prestatie, wat aantoont dat analytische verwerking van biomedische informatie *optioneel* is voor ervaren artsen.

Dit onderzoek toont aan dat de bijdrage van analytische verwerking van biomedische informatie tot het stellen van een diagnose minder belangrijk is voor ervaren artsen dan voor studenten - wat overeenkomt met de stelling over de encapsulatie van kennis door klinische ervaring. Tot zover hebben we echter alleen biomedische informatie onderzocht; hoe zit het met klinische informatie? Bovendien weten we niet in welke mate deze bevindingen kenmerkend zijn voor het onderzochte vakgebied, of voor de gebruikte onderzoeksmethode voor informatieverwerking.

Wat is de bijdrage van biomedische informatieverwerking, vergeleken met klinische informatieverwerking, bij het stellen van een hematologische diagnose?

Voor de beantwoording van deze vraag bestudeerden we informatieverwerking van studenten en arts-assistenten bij het oplossen van hematologische problemen[*]. We hebben gebruik gemaakt van “preference elicitation” om nut toe te kennen aan probleem-gerelateerde informatie - waardoor we relatief nut konden vergelijken, en bovendien het gebruik van biomedische en klinische informatie konden kwantificeren. We voorspelden dat als biomedische informatie van ondergeschikt belang is bij het stellen van de diagnose, deze later zou worden verwerkt dan klinische informatie, en niet zou moeten bijdragen tot het stellen van een diagnose. We hebben gebruik gemaakt van dezelfde vier mogelijke omschrijvingen van de bijdrage aan de prestatie als in het voorgaande onderzoek: *overbodig, essentieel, nadelig* en *optioneel*.

Het was even waarschijnlijk dat de proefpersonen het grootste nut zouden toekennen aan biomedische, als aan klinische informatie. Dat zou erop wijzen dat de gewoonte om eerst klinische en dan biomedische informatie te verwerken onderdeel is van onderzoeksvoorwaarden of van medische gewoontes. Er was een positieve relatie tussen biomedische informatieverwerking en het stellen van een diagnose, maar biomedische informatieverwerking bleek een slechte voorspeller van het stellen van een diagnose. Dit toont aan dat voor studenten en arts-assistenten de bijdrage van biomedische informatieverwerking optioneel

[*] De hematologie houdt zich bezig met afwijkingen in het bloed.

is – nuttig maar niet essentieel – bij het oplossen van hematologische vraagstukken, waarschijnlijk omdat tevens klinische informatieverwerking plaatsvindt bij het diagnosticeren.

De conclusie van dit onderzoek was dat de analytische verwerking van biomedische informatie ook bijdraagt tot het stellen van een diagnose op andere gebieden dan dat van elektrolytische en zuur-baseproblemen, en dat het kan worden onderzocht met behulp van andere technieken dan "hardopdenken". Tot op dit punt hadden we echter alleen analytische verwerking onderzocht; hoe zat het met automatische verwerking? Zijn automatische en analytische verwerking onafhankelijk van elkaar?

Beïnvloedt een initiële diagnostische hypothese de analytische informatieverwerking in niet-visuele domeinen?

Om deze vraag te beantwoorden hebben we de initiële diagnostische hypothese (een product van automatische informatieverwerking) gemanipuleerd, om het effect ervan te bestuderen op de analytische verwerking en de prestaties van arts-assistenten die een patiënt diagnosticeren met dyspnoe*, hoofdpijn en pijn op de borst. We voorspelden dat als een initiële hypothese de analytische verwerking beïnvloedt, een incorrecte hypothese het stellen van een juiste diagnose negatief zou beïnvloeden. Aan de andere kant, als analytische verwerking objectief is, en datagestuurd, dan zou het stellen van een diagnose niet beïnvloed moeten worden. Ook voorspelden we dat bij verwerping van de initiële hypothese, en beïnvloeding van de keuze van een alternatieve diagnose door eerder gestelde diagnoses, de gekozen diagnose frequenter zou moeten worden aangetroffen (of een hogere klinische urgentie zou moeten hebben) dan de verworpen hypothese. Daarentegen, als het zoeken naar een alternatieve diagnose objectief en datagestuurd is, dan zou dit niet moeten worden beïnvloed door frequentie of urgentie.

Een juiste diagnose werd vaker gesteld in gevallen waarbij de initiële hypothese juist was, wat consistent is met het beïnvloeden van analytische verwerking door initiële hypotheses. Er werd geen verband gevonden tussen klinische frequentie en urgentie, en het kiezen van een alternatieve diagnose, wat erop duidt dat het kiezen van een alternatieve hypothese gestuurd wordt door data die gebruikt wordt om de initiële hypothese te verwerpen.

Uit de resultaten van dit onderzoek hebben we geconcludeerd dat analytische verwerking plaatsvindt met een initiële diagnostische hypothese in gedachten, wat zou inhouden dat het effect van analytische verwerking op het stellen van een diagnose afhankelijk is van het resultaat van de automatische verwerking. Maar in dit onderzoek is alleen de automatische verwerking gemanipuleerd. Idealiter zouden beide variabelen moeten worden gemanipuleerd om de interactie tussen automatische en analytische verwerking te onderzoeken.

* ademnood

Verbetert training in analytische informatieverwerking het stellen van een diagnose in een visueel domein?

Om deze vraag te beantwoorden verdeelden we eerstejaars geneeskundestudenten willekeurig over drie groepen voor een training in de identificatie van dieren: één met alleen automatische verwerking; één met alleen analytische verwerking; en één met een combinatie van automatische en analytische verwerking. We gingen uit van vier mogelijke effecten van de training in analytische verwerking op het stellen van een diagnose: *essentieel*, waarbij er een verband zou moeten worden aangetoond tussen training in analytische verwerking en een verbeterde prestatie; *nadelig*, waarbij er een verband zou moeten zijn tussen het trainen in analytische verwerking en een minder goede prestatie; *overbodig*, waarbij er geen verband zou moeten bestaan tussen training in analytische verwerking en prestatie (de prestatie zou afhankelijk moeten zijn van de mate van training in automatische verwerking); en *aanvullend*, waarbij training in analytische verwerking het effect van training in automatische verwerking zou moeten versterken, en vice versa.

Er werd een verband gevonden tussen training in alleen analytische verwerking en een slechtere prestatie bij het stellen van een diagnose, wat erop wijst dat training in analytische verwerking niet essentieel is, en training in automatische verwerking niet kan vervangen. Maar bij een gelijke hoeveelheid training in analytische verwerking en automatische verwerking, verbeterde de prestatie – door automatische verwerking verbeterde de analytische verwerking. Bovendien gaf gecombineerde training eenzelfde effect als driemaal de hoeveelheid training in automatische verwerking – door analytische verwerking verbeterde de automatische verwerking. Deze resultaten stemmen overeen met het idee dat training in automatische verwerking en analytische verwerking aanvullend zijn.

Kijkend naar onze vijf onderzoeken als geheel, is de meest geschikte term voor de beschrijving van de bijdrage van analytische informatieverwerking bij het stellen van een diagnose afhankelijk van onderzoeksopzet en klinische ervaring. Als alleen analytische verwerking van biomedische informatie wordt onderzocht, lijkt het *essentieel* te zijn bij afwezigheid van klinische ervaring, maar *optioneel* bij aanwezigheid van klinische ervaring. Als het onderzocht wordt in combinatie met automatische verwerking, is de bijdrage van analytische verwerking een *voorwaarde* voor automatische verwerking. Ten slotte, wat betreft de verbetering van diagnosticering door middel van training: de effecten van training in automatische en analytische verwerking zijn *aanvullend*.

Implicaties van de resultaten van dit proefschrift

De resultaten van onze observatiestudies duiden erop dat de prestatie verbetert als belangrijke biomedische sleutelbegrippen worden gebruikt bij het stellen van de diagnose. Tegen lerenden die hun prestaties hopen te verbeteren op het gebied van elektrolytische of hematologische problemen kunnen we zeggen dat er een verband bestaat tussen analytische verwerking van biomedische sleutelbegrippen en een verbeterde prestatie - wat erop duidt dat hun prestatie zal verbeteren als zij deze begrippen beter begrijpen en kunnen gebruiken. De boodschap voor docenten is dat zij sleutelbegrippen moeten identificeren voor elke klinische presentatie (begrippen die, indien toegepast, verband houden met verbeterde prestaties), en het inzicht in begrippen moeten verbeteren, zodat de lerenden ze ook kunnen toepassen bij het diagnosticeren.

Maar analytische verwerking van biomedische informatie is geen panacee. Er bestaat niet één bepaald soort informatie of verwerking die alle problemen kan oplossen. De resultaten van onze interventieonderzoeken duiden erop dat analytische verwerking weliswaar kan compenseren voor onjuiste automatische verwerking, maar dat het stellen van een diagnose pas optimaal plaatsvindt als analytische verwerking een aanvulling is op correcte automatische verwerking. Om het stellen van een diagnose te verbeteren, zouden lerenden daarom hun begrip en gebruik van beide soorten informatie en verwerking moeten verbeteren. Medisch docenten zouden daarom holistische leerervaringen moeten creëren. Biomedische en klinische informatie vullen elkaar aan[12], evenals automatische en analytische verwerking[13] – dus onderwijs het yin én het yang.

Toekomstig onderzoek

Voortbouwend op ons huidige onderzoek, willen we de verschillen tussen *informatie* en *verwerking* met betrekking tot medische expertise verder bestuderen. Door een combinatie van het sorteren van begrippen zodat ze onderzocht kunnen worden in de statische kennis[14], en “preference elicitation” om de toepassing van begrippen bij het diagnosticeren te onderzoeken, hopen we klinische en biomedische sleutelbegrippen te identificeren voor verschillende klinische presentaties. Daarna zullen we dan door middel van interventieonderzoeken bestuderen welk effect het gebruik van deze begrippen heeft op het stellen van een diagnose.

Tot nu toe heeft het merendeel van de onderzoeken op het gebied van medische expertise zich toegespitst op het verkrijgen ervan. Even belangrijk is het onderzoek naar manieren om de leeftijdsgebonden afname van de prestatie te voorkomen.[15] We hebben ons tot doel gesteld om informatieverwerking te onderzoeken bij artsen tegen het einde van hun loopbaan, om variabelen te identificeren die verband houden met slechte diagnostische prestaties bij deze groep. Waarschijnlijk zijn de oorzaken van een slechte prestatie en dus ook de behoefte aan scholing heel anders aan deze kant van het spectrum.

Momenteel wordt de literatuur gedomineerd door opinion-based overzichtsartikelen en -boeken over het creëren van medische expertise, ook om te bepalen hoe studierichtingen moeten worden veranderd om op grote schaal kennis te produceren. Bij gebrek aan bewijs worden meningen gegeven. Evidence-based medische scholing ligt aan de horizon, maar we zijn nog ver verwijderd van het doen van evidence-based aanbevelingen voor het opzetten en onderhouden van medische expertise. Als onderzoekers van medisch onderwijs hebben we nog geen recept gevonden voor medische expertise - maar langzaam maar zeker ontdekken we wel manieren om het te vinden.

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Appendices

APPENDIX 1
Hyponatremia case

For the patient with an abnormal serum sodium concentration select the **SINGLE** most likely diagnosis from the choices A – H.

A. Artifactual (hyperglycemia)
B. Artifactual (hyperlipidemia)
C. Decreased intake of osmotically active particles
D. Diuretic-induced
E. Reduced GFR (glomerular filtration rate)
F. Gastrointestinal loss
G. Primary polydipsia
H. SIADH (syndrome of inappropriate antidiuretic hormone)

A 27-year-old female is seen in your office with a four months history of polyuria, nocturia and increasing thirst. She denies weight loss or other gastrointestinal symptoms. She has no past medical history of note and her only medication is the birth control pill. Blood pressure is 118/66 mmHg. Pulse is 72 beats per minute supine and 78 beats per minute erect. The results of investigations are shown below:

Lab values:

Serum Na+	124 mmol/L
Serum K	3.8 mmol/L
Serum Cl	92 mmol/L
Serum HCO3	20 mmol/L
Blood Urea	2.1 mmol/L
Serum Creatinine	76 µmol/L
Plasma Glucose	3.2 mmol/L
Serum osmolality	264 mosm/Kg
Urine Na	21 mmol/L
Urine osmolality	80 mosm/Kg
Arterial P_{CO2}	35 mmHg
Arterial pH	7.35

APPENDIX 2
Hyperkalemia case

For patient with an abnormal serum potassium concentration select the **SINGLE** most likely diagnosis from the choices A – G.

A. lack of insulin activity
B. reduced aldosterone activity
C. primary hyperaldosteronism
D. intracellular H+ buffering (non-anion gap acidosis)
E. cell lysis (redistribution of potassium)
F. reduced activity of Na+/K+ ATPase
G. increased K+ intake

A 62-year-old female was admitted 12 days previously for management of a diabetic foot ulcer. Her serum creatinine at that time was 84 µmol/L and serum potassium 4.6 mmol/L. She was started on clindamycin (an antibiotic) to treat the infection in her foot. Five days ago she developed diarrhea and has had at least seven episodes per day for the past three days. Her medications have been unchanged since admission (Enalapril 5 mg bid and glyburide 5 mg daily) with the exception intravenous Normal saline. She has had type II diabetes for seven years and hypertension for five years. On examination her pulse is 84 beats per minute supine rising to 96 beats per minute erect. Supine blood pressure is 108/66 mmHg. The results of investigations are shown below:

Lab values:

Serum Na (mmol/L)	130 mmol/L
Serum K (mmol/L)	5.8 mmol/L
Serum HCO3 (mmol/L)	12 mmol/L
Serum Cl (mmol/L)	106 mmol/L
Blood Urea (mmol/L)	9.2 mmol/L
Serum Creatinine (µmol/L)	112 µmol/L
Plasma Glucose (mmol/L)	9.2 mmol/L
Serum Osm (mmol/L)	282 mosm/Kg
Urine Osm (mmol/L)	330 mosm/Kg
Urine K+ (mmol/L)	68 mmol/L
Urine Cl- (mmol/L)	82 mmol/L
Urine Na	23 mmol/L
Arterial P_{CO2}	28 mmHg
Arterial pH	7.24

APPENDIX 3

Information bundles for preference elicitation for the clinical presentation of *anemia*

Clinical bundles

1. Demographics
Gender
Ethnic background
Age

2. Associated symptoms/signs
History
Clinical examination

3. Past history
Medical problems
Previous surgeries
Other problems (e.g., psychiatric)

4. Family history
Of the clinical presentation
Of other clinical presentations

5. Disease-specific risk factors (including medications)
Blood loss
Infections
Social history
Current and recent medication

Biomedical bundles

6. Red cell morphology
MCV
RDW

7. Other cell lines
WBC
Differential
Platelets

8. Reticulocyte count
Absolute count
Index

9. Hemolysis work-up (includes smear)
LDH
Haptoglobin
Total bilirubin
Unconjugated bilirubin
Other liver function tests
Blood smear
Coomb's test

10. Hematinics
Ferritin
Transferrin saturation
Folate
B12
TSH

APPENDIX 4
Scoring sheet for Preference Elicitation for the clinical presentation of *anemia*

1. Please record the number of the bundles requested in the order they are requested. If the student goes back to a bundle for additional information, or for repetition of information, then please record the bundle number again, e.g., 5, 1, 5, 7, etc.

2. Please record the presentation-specific terms that the student uses, e.g., hemolysis, breakdown, etc.

3. Please record the diagnoses that the student offers, including the final diagnosis if they then change their mind.

4. Please record additional information that the student requested that was not provided

1. Rank preference for bundles:

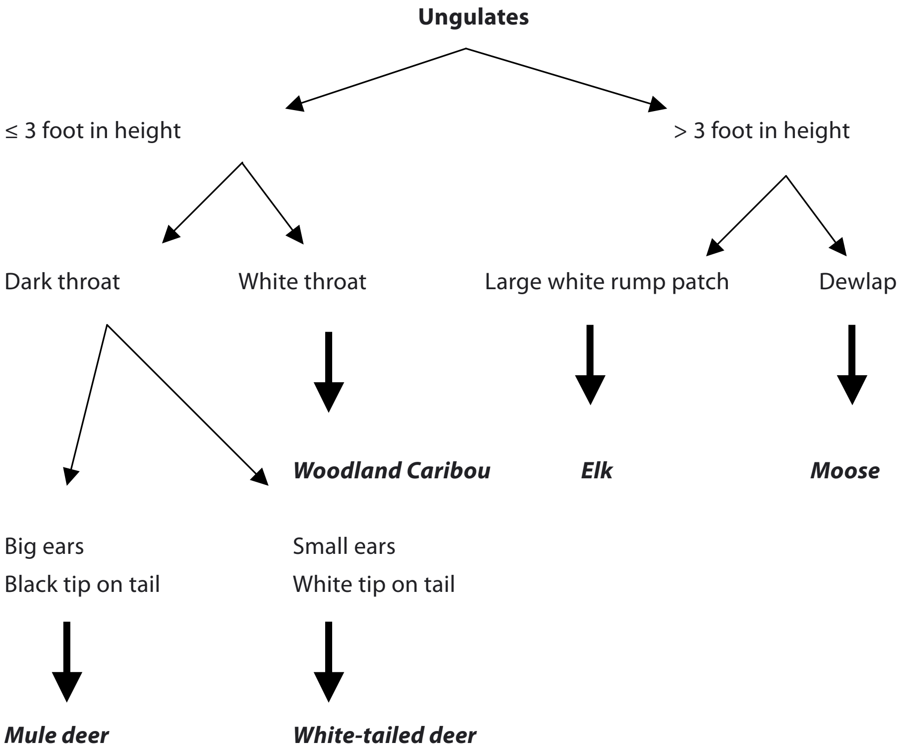
2. Presentation-specific terms used by the student

3. Diagnoses offered

4. Final diagnosis

5. Additional information requested that were not available

APPENDIX 5
Diagnostic scheme used for analytic information processing training in identification of ungulates



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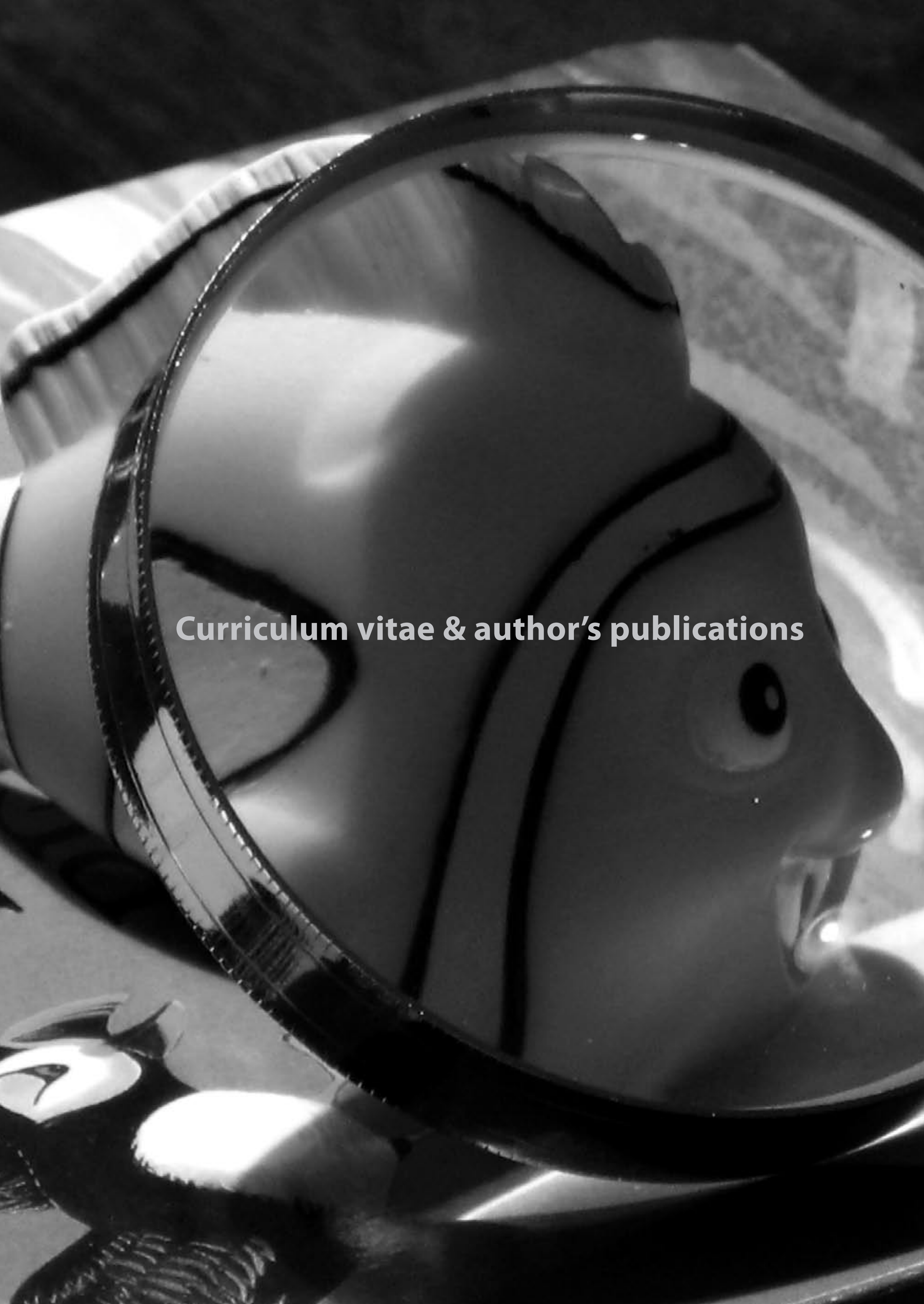

Curriculum vitae & author’s publications

CURRICULUM VITAE

Kevin McLaughlin was born in Bellshill, Lanarkshire, Scotland on May 10, 1965. He completed his medical degree – MBChB (Hons) – at the University of Edinburgh in July 1989. He completed his specialist training in Nephrology and General Medicine in October 1997 before moving to the University of Western Ontario, Canada, for a fellowship in transplantation. In January 1999 he was appointed Consultant Nephrologist at Glasgow Royal Infirmary. In September 1999 he moved to Calgary, Alberta, Canada, to take up an Assistant Professor position in the Department of Medicine. In November 2003 he received a Master's degree in Medical Education at the University of Calgary. In June 2004 he was promoted to Associate Professor. He is currently the program director for the Nephrology training program, course chair of the undergraduate Renal Course and co-chair of the objectives committee for the Medical Council of Canada. His research interests in medical education are primarily in the area of medical expertise and include the associations between knowledge structure, information processing and diagnostic performance.

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