NURSES' PROBLEM DETECTION OF INFECTION RISK: THE EFFECTS OF RISK FACTORS, EXPERTISE, AND TIME PRESSURE

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SUMMARY

Problem detection is a critical component in nursing, such that superior detection could lead to quicker intervention, even if the nature of the problem is not yet clear. A critical problem intensive care nurses typically engage in is detecting the threat of an impending hospital-acquired infection. The purpose of this study was to investigate the effects of the presence of risk factors, expertise, and time pressure on problem detection. The results suggested that time pressure seemed to have a detrimental effect on problem detection, and nurses benefitted from the presence of more risk factors. When not under time pressure, nurses were more sensitive in their problem detection judgments, and only needed one risk factor to trigger problem detection. Experienced nurses were more sensitive to the type of infection at detection, and were more likely to identify the problem correctly after information had been accumulated. These results suggest that problem detection was differentially affected by risk factors based on the presence or absence of time pressure. In addition, experienced nurses took a different approach to problem detection when compared to novices. Finally, problem detection and problem identification can in some situations occur simultaneously, but are distinct processes.

CHAPTER 1

INTRODUCTION

When working in a dynamic environment, operators will inevitably run into problems they must manage to maintain performance. The first step to managing these problems is detecting whether there is, in fact, a problem. Problem detection can be defined as "the process by which people first become concerned that events may be taking an unexpected and undesireable direction that potentially requires action" (Klein, Pliske, Crandall & Woods, 2005, p14). What is included in this definition is that a person may or may not necessarily identify the problem at this stage, thus distinguishing problem detection from problem identification (Klein et al., 2005). Problem detection is a critical component in managing performance, primarily because the quicker an operator can detect a problem, the quicker the operator can intervene (Klein et al., 2005; Woods & Sarter, 2000). Allwood (1984) found that when participants were detecting statistical errors, those who were good at detecting errors often had superior performance overall. Allwood argued that although both good and poor performers make errors, what separates the good from the bad is the ability to detect when an error is present.

There are several different approaches to explain how individuals detect a problem. At a psychological level, Drew, Evans, Vo, Jacobson and Wolfe (2012) explained how radiologists detect problems in scanned images through two competing pathways that guide visual search. The first is a selective pathway that allows the radiologist to identify objects, and the second is a nonselective pathway that allows the radiologist to understand the entire image. These two pathways together are needed to identify lesions or abnormalities, but Drew et al. argued that the nonselective pathway is critical for detecting problems by experts.

Much of the past research has concerned error detection, as opposed to problem detection. Error detection is similarly defined, such that an individual has recognized an error has occurred, without necessarily knowing what the error is (Zapf & Reason, 1994). Although error detection and problem detection are not entirely synonymous, the literature on error detection can contribute to a deeper understanding of problem detection. Past research has focused on categorizing and breaking down the processes involved in error detection, including cognitive mechanisms (Sellen, 1994), categories of detection (Konotiannis & Malakis, 2009), and detection strategies (Allwood, 1984).

The underlying mechanisms for error detection are comparable to problem detection. The literature on error detection suggests that there are two primary forces that lead to detection: internal and external. Internal detection is when an individual's expectation does not match what is occurring in the world (Allwood, 1984; Reason, 1990). For internal detection to occur, the individual must be actively involved in a task or a situation. For example, internal detection can be awareness-based, planning-based, or action-based (Kontogiannis & Malakis, 2009; Sellen, 1994). Awareness-based detection occurs when individuals revise their situation understanding, and through this revision process an error is detected. Planning-based detection occurs when the individual revises a plan for new actions, and action-based detection occurs while the action is being carried out (Kontogiannis & Malakis, 2009). All three of these detection mechanisms involve an active understanding and comparison of what is expected to what is observed in the world, and it is through this mismatch that detection occurs.

On the other hand, error detection can also occur through external processes, where an individual recognizes changes in the environment (Allwood, 1984; Blavier, Rouy, Nyssen, & DeKeyser 2005; Reason, 1990). This can be achieved through a limiting function, a third party, or an outcome (Kontogiannis & Malakis, 2009; Reason, 1990; Sellen, 1994). Limiting-functions detection is when the nature of the error prohibits any further action needed to accomplish the task from being performed (Sellen, 1994). For example, pulling the emergency brake instead of the gear shift prohibits the car from any further movement. Third party is simply when another person or automation points out the error (Reason, 1990). For example, stall alerts on aircrafts point out that the pilot has climbed too quickly. Outcome-based detection is either when the individual's expected outcome does not match what is observed, or when the individual identifies a familiar error pattern forming (Kontogiannis & Malakis, 2009; Sellen, 1994). For example, calculating a correlation coefficient greater than one alerts the person that a mistake had been made. This particular type of detection implies that detection is based on what is observed in the environment after an action is completely executed. Overall, the two detection mechanisms, internal and external, seem to suggest that error detection can either be initiated from an individual's internal expectation or triggered by the external environment.

In addition to the mechanisms involved in detection, certain characteristics of the situation also appear to have an effect. For example, in error detection, the type of error plays a role in one's ability to detect (Blavier et al., 2005; Rizzo, Bagnara, & Visciola, 1987). According to the literature, detection appears to be easiest when detecting slips, yet hardest when detecting omissions and mistakes (Blavier et al., 2005; Rizzo et al., 1987). Slips are a particular kind of error where the individual maintains the correct intention for an action, but produces an error in the execution of the planned action (Blavier et al., 2005). Therefore, quicker detection occurs because the action does not match the expectation; thus seems to be largely triggered by internal mechanisms. Mistakes, on the other hand, are a type of error that occurs because the individual has an incorrect intention, but executes the intention correctly (Blavier et al., 2005). This means that the expectation matches the outcome, but the expectation is incorrect, making detection a bit more difficult as well as more reliant on external detection mechanisms, such as limiting functions or third party. These results suggest that there are situational characteristics that can play a role in detection.

Although many problems may be rooted in error, not all problems are errors. For example, from a resilience engineering perspective, Hollnagel argued that accidents occur by concurrences of interacting components, and although all of the individual components are not in error, it is the interaction that leads a system into crossing over the safety boundary into failure (Hollnagel, 2007). Similarly, Woods and Sarter (2000) discuss the "going sour accidents," where trivial events accumulate in such a way that leads to catastrophic accidents. In other words, one small event or error could be dismissed as trivial, yet the consequences could unravel, triggering a chain of events leading to a larger unmanageable problem. This suggests that problems are not always as clear or definable as errors, thus detecting problems can be a more complex process.

There have been two predominant approaches to understanding problem detection in the literature. Cowan provided a model of *problem recognition,* defined as "how individuals in organizational contexts recognize problems" (Cowan, 1986, p763). Cowan's model involves three distinct stages: gestation/latency, categorization, and diagnosis. The gestation stage is when the problem initially begins manifesting itself in the environment, thus the human is not really involved in the process at this stage. However, the human must scan the environment to progress to the categorization stage. Categorization, in Cowan's view, is to categorize the change in the environment as either a 'problem' or 'not a problem.' To be able to make that categorization, Cowan argued that the human must reach a certain threshold of capture arousal to attempt to clarify the change in environment, which is typically done by comparing the current environment to the human's expectation of the environment. Once the human has categorized the situation as a problem, the human then searches for more information to identify or generate a plausible hypothesis for the problem. Here, Cowan is confounding problem detection with problem identification, although it is not explicitly stated whether or not the human has accurately identified the problem at the diagnosis stage. Although this model does a good job describing external detection mechanisms, it fails to fully account for internal detection mechanisms (Allwood, 1984; Blavier et al., 2005; Reason, 1990).

Klein et al. (2005), on the other hand, propose a different approach to problem detection. Although they agree with Cowan (1986) that problems arise from "disturbances" that lead to a discrepancy, they do not believe that these disturbances must accumulate to a point where the discrepancy is large enough for detection. Instead, they propose that the disturbances prompt individuals into making sense of the discrepancy, thus suggesting problem detection as more of an active and involved process (Klein et al., 2005). Klein et al. argue that the operator generates an expected state in the form of a cognitive frame. The frame therefore dictates what is considered as cues to either reinforce or contradict the expectation, and at the same time the cues from the environment guide the construction of the frame. The cues perceived from the environment can also activate related traces from memory to further generate the cognitive frame. Klein et al. (2005) argue that detection occurs when people question the existing frame based on the cues experienced, and once that questioning occurs, they can either preserve the existing frame or reframe until they understand the nature of the problem. Generally speaking, Klein et al.'s and Cowan's approaches to problem detection both include an external component where a change in the environment occurs that is undesireable. However, Klein takes a more comprehensive approach, including both internal and external mechanisms involved in detection as well as incorporates a more active approach to detection where the individual must be engaged in the situation (Allwood, 1984; Blavier et al., 2005; Reason, 1990).

Klein et al. (2005) therefore provide a comprehensive approach to how problem detection occurs in the moment. The authors then acknowledge that there are a variety of factors that affect detection, and mention that the existing literature is lacking in empirical research to understand when and how problem detection is better or worse. Thus, the current experiment attempts to take a step towards empirically uncovering the underlying factors that affect detection. However, uncovering what variables affect detection in the moment and how is only one piece of the puzzle. If and when problem detection occurs, how confident is the individual in their detection decision? Does confidence also change depending on the situational and individual variables? Does the individual know what the problem is at the time of detection, or does identification occur after the initial detection judgment? These questions, in addition to what affects problem detection, are not entirely addressed by Klein et al.'s (2005) approach.

If one views problem detection as a process of developing hypotheses about whether or not a problem exists, then problem detection as well as the associated processes can be explained by the decision-making and judgment model, HyGene (Thomas, Dougherty, Sprenger, & Harbison, 2008). HyGene states that individuals take in cues from the environment and then match those cues with traces in memory. These memory traces are then scrutinized to generate hypotheses about the situation, which are categorized as a set of leading contender hypotheses (SOC). The SOC then drives the individual's probability judgments and subsequent searches for diagnostic information to determine a single hypothesis. However, the number of traces and subsequent hypotheses that are retained depends on both task characteristics and cognitive limitations. The HyGene model therefore incorporates Klein et al.'s (2005) approach, such that cues are actively considered, and subsequent cues can either reinforce or contradict a particular hypothesis. HyGene also addresses the fact that both internal (cognitive limitations) and external (task characteristics) affect detection. However, HyGene also considers how those factors drive future behaviors and judgments, thus provides a more exhaustive approach.

It is important to note that problem detection in dynamic environments can be quite difficult. Moray (1981) explored several different characteristics of dynamic environments that affect detection. For example, operators are typically receiving information from multiple information sources, which are typically changing and interacting in complex ways (Moray, 1981). In addition, much of the information the operator is receiving can be ambiguous or missing (Moray, 1981). Detection can also vary depending on the nature of the problem. Problems can range from being completely unexpected and unmanageable to routine and easily solvable. The current experiment focused on a particular type of problem in-between the two extremes; one where operators are trained to handle, yet does not occur routinely. Hospital-acquired infections (HAIs) are an interesting problem in the healthcare industry that is gaining attention. Any patient in a hospital runs the risk of developing an HAI, yet research is still trying to understand how HAIs occur and how they can be avoided. The current experiment therefore selected the problem of the development of HAIs in an attempt to uncover how nurses detect and identify the threat of an HAI.

HAIs are a dangerous problem in the healthcare industry, typically leading to an increase in patient length of stay and increased healthcare costs for both patients and hospitals (Kohn, Corrigan, & Donaldson, 2000). Additionally, the incidence of HAIs is increasing to an alarming rate, with studies reporting as many as 1.7 million American patients per year (Klevens et al., 2007). The more common HAIs to date include central line-associated bloodstream infections (CLABSI), catheter-associated urinary tract infection (CAUTI), clostridium difficile (c diff), surgical site infection, methycillin-resistant staphylococcus aureus (MRSA), and ventilator-associated pneumonia (VAP) (Center for Disease Control, 2012). CLABSIs are a particularly deadly infection, resulting in over 30,000 estimated deaths in the US alone (Klevens et al., 2007). Additionally, it is estimated that around 59% of patients in the intensive care unit (ICU) and 24% of patients not in the ICU have had a central venous catheter placed during their stay in a hospital, thus the opportunity for contracting a CLABSI is particularly high for patients in the ICU (Climo, Diekema, Warren, Herwaldt, & Perl, 2003). In fact, Marschall et al. (2007) estimated that of the patients who have central venous catheters in an ICU, the rate of actually developing a CLABSI is 5.2 per 1,000 catheter days. Thus, the risk runs high for a patient to develop a CLABSI, particularly if they are in an ICU. However, many of the CLABSIs that occur are preventable (Center for Disease Control, 2011).

Because CLABSIs are by and large considered a preventable disease (Center for Disease Control, 2011), a variety of efforts have been made to reduce the incidence of CLABSI. For example, evidence-based best practices for managing a central line have been established in order to prevent infection (Hughes & Collins, 2008; Marschall et al., 2008). These include strategies such as using hand hygiene, chlorhexidine-based antiseptic, maximum barriers, changing the dressing and insertion site, and using checklists for these dressing changes, to name a few (Marschall et al., 2008). These strategies can also be combined into one functional unit, referred to as "care bundles" (Costello, Morrow, Graham, Potter-Bynoe, Sandora & Laussen, 2007). Many of these practices are emphasized through educational programs and surveillance (Marshall, 2007). However, these strategies are implemented to prevent CLABSI from occurring, but of course these strategies do not address the process of detecting the problem of an impending CLABSI.

Another area of infection research has attempted to address this problem by identifying the risk factors that put a patient at an increased risk of developing a CLABSI.

For example, one major factor is how long the patient has a central line placed (Advani, Reich, Sengupta, Gosey, & Milstone, 2011; Kelly, Conwaym Wirth, Potter-Bynoe, Billet, & Sandora, 2011; Sengupta et al., 2010; Wylie et al., 2010). Sengupta et al. found that the risk of developing a CLABSI changes depending on the number of days a peripherally inserted central catheter (PICC) line is placed. Specifically, they found that within the first 18 days of placing a PICC line, risk of infection increased at a rate of 14% per day. From day 18 to 35, the risk of infection decreased, but after day 35, risk increased again at a rate of 33% per day (Sengupta et al., 2010). Thus, the number of days the line is placed changes the amount of risk of developing an infection. Other risk factors include whether patient is in the ICU, whether the line was placed in the ICU, how many catheters are placed, and where the lines are placed (Advani et al., 2011; Wylie et al., 2010). Specifically, if two or more catheters are placed in the ICU and if there are lines inserted in the lower parts of the body (such as the femoral vein), risk is increased (Advani, 2011; Wylie, 2010). There are several other characteristics of the patient that result in an increased risk for developing an infection. For example, if the patient has non-operative cardiovascular disease, an underlying malignancy, or an underlying metabolic condition, the risk of developing an infection is increased (Advani et al., 2011; Wylie et al., 2010). Also, if the patient has had parenteral nutrition, blood transfusions, or a gastronomy tube, they will have increased risk (Advani et al., 2011; Kelly et al., 2011; Wylie et al., 2010).

The rather extensive list of risk factors that have been identified for predisposing a patient towards developing a CLABSI (or any other HAI) implies that health care providers should be attending to and acknowledging these risk factors. Thus, the proposed experiment aims to examine whether the presence of risk factors does in fact trigger problem detection.

The particular provider population of interest for the current study is the nurses working in the NICU. Nurses are typically on the front lines in terms of managing patient care. One study found that nurses made as many as 238 decisions over a two-hour period (Bucknall, 2000). Nurses spend a considerable amount of time with their patients managing their care, and thus their ability to detect problems is critical. Again, because nursing is such a dynamic environment, detecting problems becomes more difficult. However, it is hypothesized that the relative experience of the nurse will affect detection.

A variety of both qualitative and quantitative differences exist between experts and novices (Benner, 1982; Benner, Tanner, & Chelsa, 2009). For example, experts tend to be superior in terms of managing dynamic situations by making contingency plans and preparing for unforeseen events (Xiao, Milgram, & Doyle, 1997). In addition, experts can recognize patterns better and thus are better at detecting abnormalities (Ericsson, Charness, Feltovich, & Hoffman, 2006). This implies that expert nurses are better equipped to manage the ambiguity in their environment, which could compensate for detection difficulty (Moray, 1981).

Experts perceive patterns in more meaningful ways than novices as well as generate superior mental models (Ericsson et al., 2006; Hutton & Klein, 1999). This implies that experts should have not only a clearer understanding of the observed and expected state, but they should recognize the presence of the risk factors as more meaningful and important when compared to novices.

In addition to having a clearer expected state, experts tend to be more able to adjust plans and expectations in the face of new information (Waag & Bell, 1997). This suggests that experts should therefore be better at reframing a situation as problematic in the face of discrepant information according to Klein et al. (2005). Klein et al. also highlight the notion that experts are not only better at detecting problems, particularly with the more subtle cues, but also have stronger expectancies associated with these cues. Thomas, Dougherty, Sprenger, & Haribson (2008) have also found differences in decisions and judgments based on the level of experience. Finally, some studies have found that experts generally perform quicker and make fewer errors than novices (Hutton & Klein, 1999), suggesting that experts should then also be able to detect problems more quickly and more accurately. However, it has also been found that experts often spend more time assessing situations when compared to novices (Ericsson, et al., 2006). This could imply that although experts may be faster at detecting a problem, they may take longer to appropriately identify the problem.

Based on these findings, it would make sense that experts should be superior in their problem detection. It has been shown that expertise does in fact play a role in detection. For example, Kundel and Nodine (1975) found that radiologists were able to detect lesions in chest radiographs 70% of the time in under one fifth of a second. Thus in such a short amount of time, expert radiologists were able to detect better than chance whether there was a problem. Drew et al. (2012) argued that expertise plays a role because expert radiologists know where to look, thus guiding their detection search strategies. This information taken together suggests that expertise, in addition to the presence of risk factors, should play a role in nurses' detection of an impending infection.

Expertise is typically operationalized based on performance outcomes (Ericsson, Whyte, & Ward, 2007). However, because performance records were unavailable, years of experience was used as a surrogate for expertise. A previous study evaluating NICU nurses' risk assessment was successfully able to elicit differences based on years of experience (Militello, 1995), thus a similar approached was used for this experiment.

In addition to varying levels of expertise, it was hypothesized that time pressure will play a role in problem detection. Time pressure occurs frequently in the health care environment, which results in a restricted range of options or strategies to perform their work (Hassall & Sanderson, 2012). Under time pressure, operators tend to switch to more rule-based heuristic strategies (Hassall & Sanderson, 2012; Rothrock & Kirlik, 2003). In addition, Dougherty and Hunter (2003b) found that individuals generate fewer hypotheses and report higher probability judgments while under time pressure compared to no time pressure. Therefore, it is suggested that similar approaches will be taken in detection, such that nurses will tend to use these heuristic short-cuts, thus leading them to detect a problem faster than when they had the ability to take their time.

However, it was also hypothesized that nurses would not be as accurate in their identification judgments when placed under time pressure. It has been shown that individuals will choose to perform strategies that minimize time and effort (Gray, Sims, Fu & Schoelles, 2006), and thus when placed under time pressure, trying to identify the problem may be too laborious whereas detecting whether there is a problem can be less so. Nurses have in fact developed strategies for managing time pressure (Bowers, Lauring & Jacobson, 2000), but the strategies nurses use to detect problems have not yet received scientific scrutiny.

Overall, the current experiment aimed to examine several hypotheses. The first hypothesis was that nurses would more readily to detect a problem of an impending infection if the patient possessed more risk factors. The more risk factors present, the more cues available to lead the individual to reframe the situation as problematic.

Second, it was hypothesized that problem detection would be better among experienced nurses than when compared to less experienced nurses. Experienced nurses would more readily recognize the risk factors as cues to a problem (Drew et al., 2012), thus would be both faster and more accurate in detecting problems. It was also hypothesized that experienced nurses would be less reliant on more risk factors to detect a problem compared to novices. This was because expert nurses should have greater expectancies and more memory traces with all the risk factors presented (Hintzman, 1988; Klein et al. 2005), and so detection performance should be high even when only one risk factor is present, perhaps resulting in little room for improvement. However, for less experienced nurses, more cues would be more useful in generating a clearer hypothesis.

Nurses should also be faster to make a problem detection response when under time pressure when compared to no time pressure, although problem identification accuracy may be impaired. Because nurses will be forced to make a decision in such a small amount of time, nurses may be more likely to say there is a problem before generating a clear hypothesis. However, these time constraints could impair accurate identification. In addition, it was hypothesized that experienced nurses would be less affected by time pressure when compared to novices because the experienced nurses have superior mental models associated with the cues (Ericsson et al., 2006; Hutton & Klein, 1999).

It was also anticipated that in the presence of multiple risk factors, experienced nurses under time pressure would detect problems the fastest. This was hypothesized because the more cues presented, the more traces are activated among experts leading to faster detection, which is further facilitated by the notion that experts are more adaptable in managing the time pressure. On the other hand, novices would have less frames associated with the cues, so fewer frames and fewer cues available should impair detection. Also, because novices are less adaptable to the changing environment, they would perform the worst under time pressure.

In terms of problem identification, it was hypothesized that in the presence of multiple risk factors, experienced nurses not under time pressure would be most accurate in problem identification. This is because experienced nurses have superior mental models with more frames associated with each cue, and the absence of time constraints should allow these nurses to carefully evaluate the cues. On the other hand, it was hypothesized that in the presence of one risk factor, novice nurses under time pressure would be least accurate in problem identification.

CHAPTER 2

METHOD

Participants

Participants were nurses working in the Neonatal Intensive Care Unit (NICU) at the Medical Center of Central Georgia (MCCG) in Macon, GA. A total of 24 nurses (all female) participated in this study, and were compensated $25 for one hour of participation. Participants' ages ranged from 22-55 years of age. Experienced nurses were categorized as nurses working in the NICU for at least 10 years at MCCG (*M*=18.33 years, *SD*=5.97), whereas novice nurses were categorized as nurses working in the NICU for less than two years (*M*=1.29 years, *SD*=0.78). Previous research has demonstrated differences in experienced and novices by grouping nurses with more than five years of experience and less than three years respectively (Militello, 1995), thus the grouping used in the current experiment was deemed sufficient. Nurses were recruited via nurse managers.

Design

The experiment was a 2 (Time pressure: time pressure, no time pressure) x 2 (Experience: experienced, novice) x 2 (Risk factors: one risk factor, three risk factors) x 3 (Infection Type: CLABSI, Other HAI, None) mixed design. Time pressure and experience were between subjects variables, and risk factors and infection type were within. Before the experiment began, participants were randomly assigned to a time pressure condition.

Stimuli and Apparatus

Apparatus

The experiment was controlled using E-Prime 2.0. E-Prime was run on a laboratory-owned laptop and recorded participant responses as well as reaction times and durations for each response.

Case Study Construction

A total of 18 case study templates were constructed in collaboration with experienced nurses in the NICU. Half of the templates pertained to patients with a CLABSI, and the other half pertained to patients with other types of HAIs. Each of these individual templates contained seven neutral facts about the patient and three risk factors. Templates were initially derived from patient reports, but were completely de-identified of any personal information. From there, the individual facts pertaining to each case study were revised to generate enough neutral and risk factor facts.

Templates were then used to generate individual case studies for each risk factor condition, each containing seven facts (see Table 1). The One Risk Factor condition contained six neutral facts and one risk factor, the Three Risk Factors condition contained four neutral facts and three risk factors, and the None condition contained seven neutral facts and no risk factors. Each case study was arranged in the same structure, such that the first, second, and last fact contained neutral facts (non-risk factors). These particular neutral facts were identical across the One Risk Factor, Three Risk Factors, and None within a template.

For each family, one risk factor was randomly selected to appear in both the one risk factor and three risk factors condition, which was yoked across conditions. For the One Risk Factor condition, this yoked risk factor was randomly selected to appear in either the third or fourth fact within a case study. For the Three Risk Factor conditions, the yoked risk factor appeared as the last of the three risk factors. The other two risk factors were randomly slotted, with the first risk factor appearing in the same position as it did in the One Risk Factor condition. This meant that in the Three Risk Factor conditions, the participant was not exposed to the yoked risk factor until the participant had seen the other two risk factors to measure how additional risk factors in addition to the one risk factor affects detection. An example layout for each condition within a family is presented in Table 1. All case studies are presented in Appendix B.

Table 1

Sample Layout of One, Three, and no Risk Factors Conditions for a CLABSI Family.

One Risk Factor	Three Risk Factors	None
Day of Life 23	Day of Life 23	Day of Life 23
Adjusted Gestational Age 35 weeks	Adjusted Gestational Age 35 weeks	Adjusted Gestational Age 35 weeks
PICC line day 21	**Very low birth weight**	Isolette
On NC 2 IL 21-25%	On NC 2 IL 21-25%	On NC 2 IL 21-25%
NPO	**Preterm labor**	NPO
Hypothermia	**PICC line day 21**	Hypothermia
Black Male	Black Male	Black Male

Note. Risk factors appear in bold. Each participant was exposed to only one of these case studies.

Each case study generated within a family was presented to different participants as a way to constrain the impact of the individual case study content. A demonstration of this method is displayed in Table 2. A nurse educator and nurse practitioner validated case studies by sorting each case study into CLABSI, other HAI, and None. Revisions and refinements were provided until agreement was reached.

Table 2

Proposed Distribution of Case Studies Across Conditions and Participants for CLABSI Condition.

	1 Risk Factor	3 Risk Factors	None
Participant 1	A	B	C
Participant 2	B	C	A
Participant 3	C	A	B

Note. Letters A, B, and C Represent case study families that were transformed to the appropriate condition. Procedure was identical for the other HAI condition.

The total number of case studies per experimental condition per participant is displayed in Table 3. This resulted in a total of 36 cases per case study-type (CLABSI, other HAI, None). For the case studies that led to a CLABSI or other HAI problems, half of the case studies contained three risk factors and half of the case studies contained one risk factor.

Table 3

Proposed Number of Cases For Each Condition

	Time Pressure		No Time Pressure	
Case Study	Experienced	Novice	Experienced	Novice
CLABSI	36	36	36	36
3 Risk Factors	18	18	18	18
1 Risk Factor	18	18	18	18
Other HAI	36	36	36	36
3 Risk Factors	18	18	18	18
1 Risk Factor	18	18	18	18
Non-HAI	36	36	36	36

Instructions

Nurses were provided with two forms of instructions. The first form was a general set of instructions that explained the task and the purpose of the experiment. These instructions were in paper format and were available to the nurse throughout the experiment to be used as a reference, and is provided in Appendix A.

In addition to a paper copy of the instructions, another set of instructions appeared on the screen immediately before the experiment began. A sample of the online instructions appears in Appendix B.

If the nurse was assigned to the time pressure condition, there were additional sentences that read, "Assume you have a high patient load and have other more acute patients to monitor. Therefore, it is important to work through each case study as quickly as possible so you can attend to your other patients. Your responses will be timed and your elapsed time will be displayed." Another screen appeared after the original instructions page that reminded participants once more that time will be recorded and therefore should work through each case study as quickly as possible.

Case Study Content

An example of a case study appears in Appendix C. Appendix C displays the series of screens the nurse was exposed to throughout each case study. This example case study is for a participant in the no time pressure condition, thus the additional information pertaining to time pressure does appear. The second screen in Appendix C is the first screen of a case study. The top of the screen shows the first neutral fact about the patient, and the bottom of the screen asks the nurse "Is this patient at risk for infection?" If the nurse decided that the patient is at increased risk, the nurse should select the "Yes" button. If the nurse decided that the patient is *not* at an increased risk, the nurse selects "Continue" to receive the next fact. In the example in Appendix C, the nurse decided the patient is at increased risk after the fifth fact was presented.

Once this button was selected, the nurse was prompted to answer three questions pertaining to her decision: problem detection confidence, problem identification, and problem identification confidence. Once these three questions were answered, the nurse continued to receive the next fact and the problem detection question disappeared. When the nurse had read the new fact and was ready to move on, the nurse answered the same confidence and identification questions. These questions were answered based on the new information acquired after the nurse had already detected the problem. This procedure continued until all seven facts have been presented. After all seven facts were presented, the nurse was prompted to identify the probability that the patient will develop an infection. This question was presented at the end of each case study regardless of whether the nurse selected "Yes."

Measures

Problem Detection

Problem detection was measured in two ways. The first problem detection measure was the total time from the time the first fact appears on the screen at the beginning of each case study to the time the nurse selects "Yes." In addition to how long it took the nurse to detect a problem, the number of facts needed to detect the problem was also recorded. However, the yoked risk factor appeared in different positions across conditions. Thus, the type of risk factor can potentially confound this measurement. Regardless, the total time-to-detect was compared across all experimental conditions.

The second problem detection measure was the total time the yoked risk factor is presented to the nurse. Thus, from the time the screen with the yoked risk factor is presented to the time the nurse either selected “yes” or continued to the next screen was recorded. For example, the time for the risk factor “PICC line day 21” from Table 3 was measured in both the one and three risk factor conditions. This time measurement was compared between the one versus three risk factor case studies for both CLABSI and other HAI conditions. Because the yoked risk factor was the identical across conditions, it allowed us to compare any potential benefit of additional risk factors.

In addition to time measurements, nurses also provided confidence ratings in their decisions immediately after selecting “Yes” as well as after each other fact subsequently presented for the rest of the case study. Confidence ratings were recorded and analyzed for each case study.

Problem Identification

After the nurse selected “Yes,” making an affirmative problem detection judgment, and provided a confidence rating, the nurse was also asked to identify what they thought was wrong with the patient. This question was asked immediately after detection as well as after each remaining fact for the rest of the case study. Identification accuracy was analyzed at detection and after more information becomes available. Once the nurses identified the problem, they were asked to provide another confidence rating in their identification. These confidence ratings were also presented immediately after selecting "Yes" as well as after every other fact.

Infection Probability

Nurses were asked to estimate the probability that the patient would develop an infection. This question was asked at the end of each cases study regardless of whether or not the nurse detected a problem. Thus, nurses provided a probability judgment for each individual case study.

Questionnaire

After all case studies were completed, nurses were instructed to complete a post study questionnaire. The post study questionnaire attempted to elicit any strategies used for detection. The questionnaire also attempted to elicit which cues were more important than others. The questionnaire was electronically administered; a copy of the questionnaire appears in Appendix D.

Procedure

When the nurses arrived, they were given a consent form and had the opportunity to read and ask questions about the experiment. Once informed consent was obtained, the nurse was presented with both the paper and online instructions. Nurses engaged in two practice trials to familiarize themselves with the task. The experimenter worked through the practice case studies with the nurse and answered any questions about the experiment. The content of the practice case studies was identical for all nurses. Once the practice case studies were completed, the experiment paused and the experimenter asked the nurse if she had any remaining questions. If the nurse was in the time pressure condition, the experimenter reminded the nurse to work as quickly as possible and the responses would be timed. If there were no remaining questions, the nurse was instructed to begin.

Each nurse performed the same tasks for all 18 case studies. Each case study was presented in a same format as the screens presented in Appendix C. After the nurse completed a case study, a screen was presented for five seconds informing the nurse that the particular case study was complete. Each case study was presented in a random order for each participant. After the nurse completed all case studies, the experiment closed and the nurse was administered the post-study questionnaire. Finally, nurses were compensated for their participation and the experiment concluded.

CHAPTER 3

RESULTS

Manipulation Check

To ensure that the manipulation of time pressure was sufficient, a manipulation check was performed by analyzing the time spent on the cues. Average time spent on the cues excluding the time spent on answering questions was calculated for each case study for each participant. Time spent on answering questions was excluded since reading and typing speed is confounded with cognitive processing speed. These times were analyzed using an independent sample T-Test for each level of Time Pressure. Means and standard deviations are presented in Appendix E. Results indicated that there was a significant effect of Time Pressure, such that participants spent less time on cues while under time pressure, $t(22)=2.394$, $p<.05$. Mean time spent on cues for each level of time pressure is displayed in Figure 1.

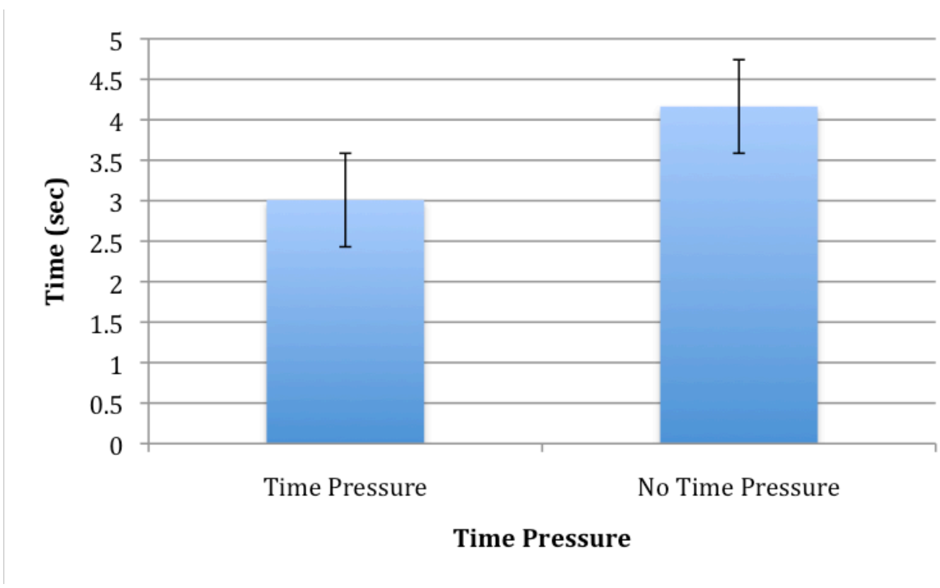

Figure 1. Mean time spent on cues for each level of time pressure.

Overall, participants spent more time on the cues when not under time pressure than when under time pressure. Thus, time pressure was considered an appropriate variable to conduct further analyses, including more precise evaluations of the cues.

Problem Detection

Detection Sensitivity

Sensitivity analyses were conducted to determine when nurses were detecting a problem, and how their detections varied across experimental conditions. Although there were signal and non-signal case studies (e.g., cases that included a risk factor and cases that contained all neutrals), detection on signal trials could not always be considered a "hit" in the signal-detection theory sense if the nurse detected a problem before any risk factors appeared. Thus, calculating d primes for each trial was not considered an appropriate metric.

Instead, cumulative detection was used to assess detection sensitivity. For each condition, cumulative detection was calculated along the cues. In other words, each case study was scored based on when along the case study the nurse detected a problem. An example of this scoring process is displayed in Table 4. Each experimental condition containing risk factors had a total of three case studies for each nurse. For the One Risk Factor condition, this nurse (mistakenly) detected a problem at the first neutral fact (N1) in the first case study, detected a problem at the risk factor (RF1) in the second case study, and did not detect a problem on the third case study (see Column 1, Table 4). For the Three Risk Factor condition, this nurse detected a problem at the first neutral fact (N1) in the first case study, detected a problem at the second risk factor (RF2) in the second case study, and detected a problem at the third risk factor (RF3) in the third case study (see Column 2, Table 4).

For case studies in the None condition (containing all neutrals), there were a total of six case studies for each nurse. Neutral cues located in the same position as the risk factors were included to compare cumulative detection between signal and non-signal trials. In column 3 in Table 4, the nurse detected a problem at the second neutral fact (N2), and did not detect a problem in the remaining five case studies. These scores were then plotted across the cues for each condition.

Table 4

Cumulative Detection Scoring

One Risk Factor	Three Risk Factors	None
N1 (1) [a]	*N1 (1)*	*N1 (0)*
N2 (1)	*N2 (1)*	*N2 (1)*
RF1 (2) [b]	**RF1 (1)**	**N3 (1)**
	RF2 (2)	**N4 (1)**
	RF3 (3)	**N5 (1)**

[a] First neutral fact where the nurse mistakenly detected a problem in the first case study. [b] First risk factor where the nurse detected a problem in the first risk factor. Numbers in parenthesis represent cumulative scoring. Items in bold represent risk factors or equivalent neutral facts for None condition.

The cumulative detection scores were averaged across all nurses for each experimental condition. For the None condition, cumulative detection scores were divided in half to allow for equal comparison across all conditions. These cumulative detection scores were then plotted across the cues for each condition, and are displayed in Figure 2. Follow-up analyses further examining signal and no signal trials are discussed in following sub-sections.

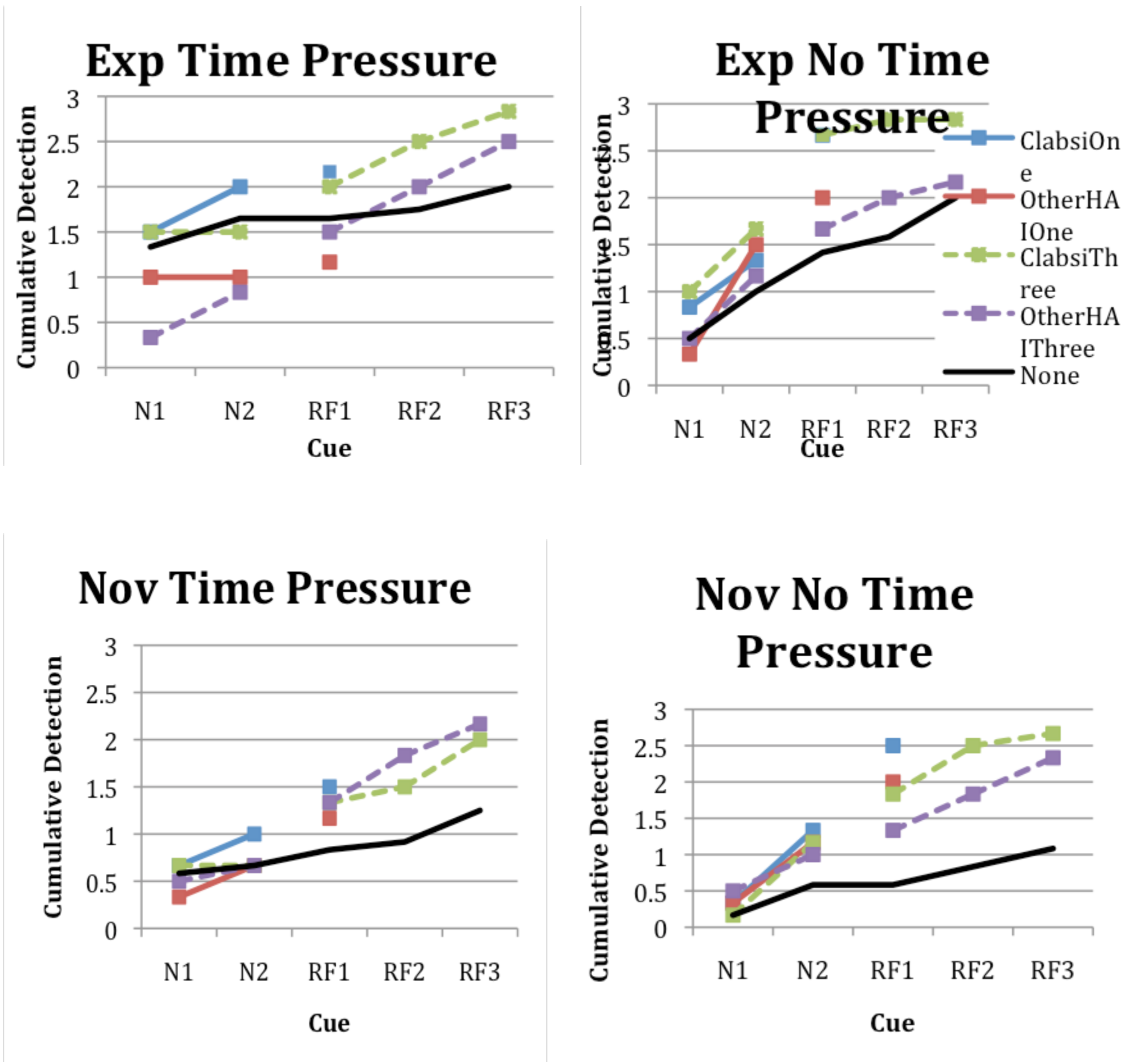

Figure 2. Cumulative detection across cues for each between subjects condition.

Average cumulative detection is displayed in Figure 2 for each between-subjects condition. One Risk Factor conditions are displayed as solid broken lines and Three Risk Factor conditions are displayed as dashed broken lines. The black solid line indicates the None condition. Generally speaking, cumulative detection was higher for signal trials than non-signal trials. Overall, cumulative detection was lower for the None condition than the Risk Factor conditions. This was also generally true comparing the initial neutral facts with the risk factors *within* a case as well. In fact, the initial neutral facts were roughly similar to the initial neutral facts of the None condition. The following sections discuss further analyses of the results displayed in Figure 2. I begin with an analysis of the None conditions (black line) in Figure 2.

<u>No-Signal-Trial-Detection</u>

To provide a baseline assessment of nurses' problem detection sensitivity using this procedure, cumulative detection was examined for the None condition. A 2(Experience) x 2(Time Pressure) x 5(None Cue Position) mixed ANOVA was used to evaluate whether experience or time pressure produced differential effects on detection when no signal was present. The results revealed a significant Mauchly's test of sphericity, thus the Huynh-Feldt approach was employed to adjust for epsilon. Means and standard deviations are displayed in Appendix E. A significant main effect was found for None Cue Position, $F(4,80) = 19.965$, $p < .01$, $\eta_p^2 = .496$, indicating that cumulative detection varied across the five none cues. Tests of within-subjects contrasts revealed a significant linear effect $F(1,20) = 35.862$, $p < .01$, $\eta_p^2 = .642$, as well as a significant cubic effect, $F(1,20) = 4.865$, $p < .01$, $\eta_p^2 = .196$. Because we were looking at cumulative detection, the line should never be decreasing and therefore, if anything, increases are likely as more problem detection judgments are made. The cubic effect however, demonstrates that cumulative detection increases from N1 to N2, then levels off slightly from N2 to N4, and then increases again from N4 to N5. The slight increase in sensitivity could be due to the nurses' expectation of a risk factor to occur. However, it should be noted that by N4 and N5, cumulative detection is always below signal trials by this point. In addition, there were no significant main effects or interaction effects of time pressure or experience, thus detection in the None condition was the same regardless of experience or time pressure.

<u>Signal-Trial Detection</u>

A separate assessment was conducted only on trials containing risk factors at some point in the trial. A 2(Experience) x 2(Time Pressure) x (Infection Type) x 2(Risk Factors) x 2(Cue Type: Neutral, Risk Factor) Mixed ANOVA was used to examine if cumulative detection significantly increased when a risk factor was presented, as well as how cumulative detection varied across conditions. To accomplish this, cumulative detection on N1 and N2 were averaged for each condition, generating the Neutral Cue Type. For the One Risk Factor conditions, the neutral cue was compared against cumulative detection on the one risk factor. For the Three Risk Factor conditions, the neutral cue was compared against cumulative detection on the third risk factor. Results from the ANOVA are displayed in Table 5, with means in Figure 2. Means and standard deviations are also reported in Appendix E.

Table 5

Significance Tests for Cumulative Detection Sensitivity

Variable	F	df	p	η_p^2
Cue Type	118.39	1, 20	.000**	0.855
Risk Factors	9.66	1, 20	.006**	0.326
Infection Type	15.53	1, 20	.001**	0.437
Experience	1.43	1, 20	.245	0.067
Time Pressure	0.57	1, 20	.459	0.028
Experience x Time Pressure	0.37	1, 20	.55	0.018
Cue Type x Time Pressure	4.50	1, 20	.047*	0.184
Cue Type x Experience	0.59	1, 20	.452	0.029

Table 5 continued

Risk Factors x Experience	0.01	1, 20	.943	0.000
Risk Factors x Time Pressure	2.76	1, 20	.112	0.121
Infection x Experience	4.84	1, 20	.040*	0.195
Infection x Time Pressure	0.21	1, 20	.650	0.010
Cue Type x Risk Factors	14.85	1, 20	.001**	0.426
Cue Type x Infection	0.40	1, 20	.537	0.019
Risk Factors x Infection	0.53	1, 20	.475	0.026
Cue Type x Experience x Time Pressure	0.10	1, 20	.755	0.005
Risk Factors x Experience x Time Pressure	0.05	1, 20	.831	0.002
Infection x Experience x Time Pressure	0.59	1, 20	.452	0.029
Cue Type x Risk Factors x Experience	0.19	1, 20	.663	0.010
Cue Type x Risk Factors x Time Pressure	6.71	1, 20	.018*	0.251
Cue Type x Infection x Time Pressure	2.04	1, 20	.169	0.092
Cue Type x Infection x Experience	0.03	1, 20	.866	0.001
Risk Factors x Infection x Experience	0.29	1, 20	.600	0.014
Risk Factors x Infection x Time Pressure	0.53	1, 20	.475	0.026
Cue Type x Risk Factors x Infection	2.04	1, 20	.169	0.092
Cue Type x Risk Factors x Experience x Time Pressure	1.44	1, 20	.244	0.067
Cue Type x Infection x Experience x Time Pressure	0.003	1, 20	.955	0.000
Risk Factors x Infection x Experience x Time Pressure	0.06	1, 20	.811	0.003
Cue Type x Risk Factors x Infection x Experience	0.85	1, 20	.367	0.041
Cue Type x Risk Factors x Infection x Time Pressure	0.57	1, 20	.459	0.028
Cue Type x Risk Factors x Infection x Experience x Time Pressure	0.06	1, 20	.804	0.003

Note: * = $p<.05$
** = $p<.01$

Results for the significant three-way interaction between Cue Type, Risk Factors, and Time Pressure are displayed in Figure 3. A post-hoc analysis was conducted to analyze the lower-order two-way interactions at each level of time pressure separately. Under time pressure, a significant two-way interaction was found between Risk Factors and Cue Type, $F(1,10) = 28.457$, $p<.01$. Under no time pressure however, there was no significant two-way interaction between Risk Factors and Cue Type, $F(1,10) = .628$, $p=.446$.

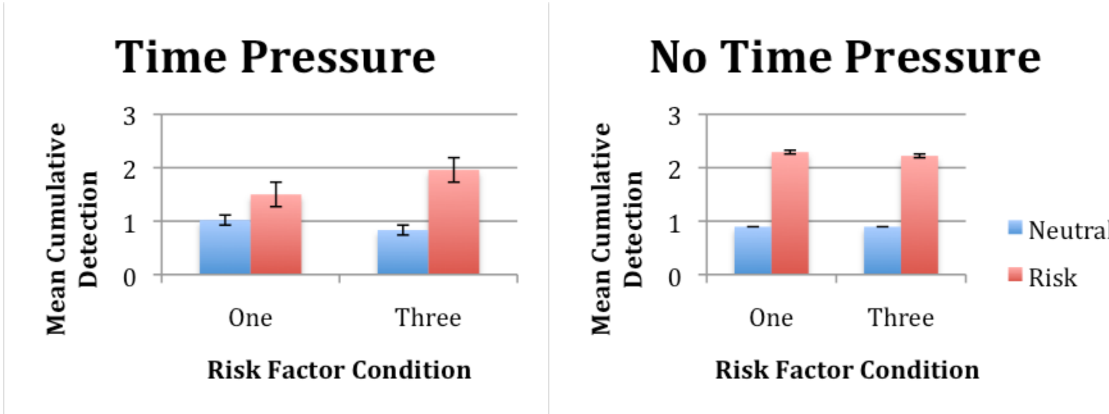

Figure 3. Mean cumulative detection for the three-way interaction between Time Pressure, Risk Factors, and Cue Type with standard error bars.

While under time pressure, nurses' sensitivity to detecting a problem on the risk factors varied depending on the risk factor condition. As shown in the graph on the left side of Figure 3, cumulative detection is higher than neutrals on both the one and three risk factor conditions, with cumulative detection highest in the three risk factor condition. This suggests that even under time pressure, nurses are able to distinguish the risk factors as a signal, but also benefit from a second or third risk factor in their problem detection judgments.

Under no time pressure, nurses' problem detection on neutral facts was also equal between the one and the three risk factor conditions. However, as shown in the graph on the right side of Figure 3, cumulative detection is the same across one and three risk factor conditions for both neutral and risk factors. Again, cumulative detection is higher on the risk factors compared to the neutrals, but nurses' did not benefit from the additional risk factors in their problem detection judgments in the absence of time pressure. With only a single risk factor, nurses' detection was already quite high when they are given time to consider the cue.

In addition to the three-way interaction, a significant two-way interaction was also found between Experience and Infection Type (Figure 4). This interaction shows that the main effect of infection type—more frequent detection of CLABSI—was especially evident among the experienced nurses. This is perhaps due to experienced nurses' superior ability to recognize individual infection types, but it is also likely that detection sensitivity is higher for CLABSI because the experience distinguishing our nurse groups is experience with the more common infection, CLABSI. CLABSI is a more common threat in the MCCG NICU, thus more experienced nurses may have had more exposure to CLABSI patients.

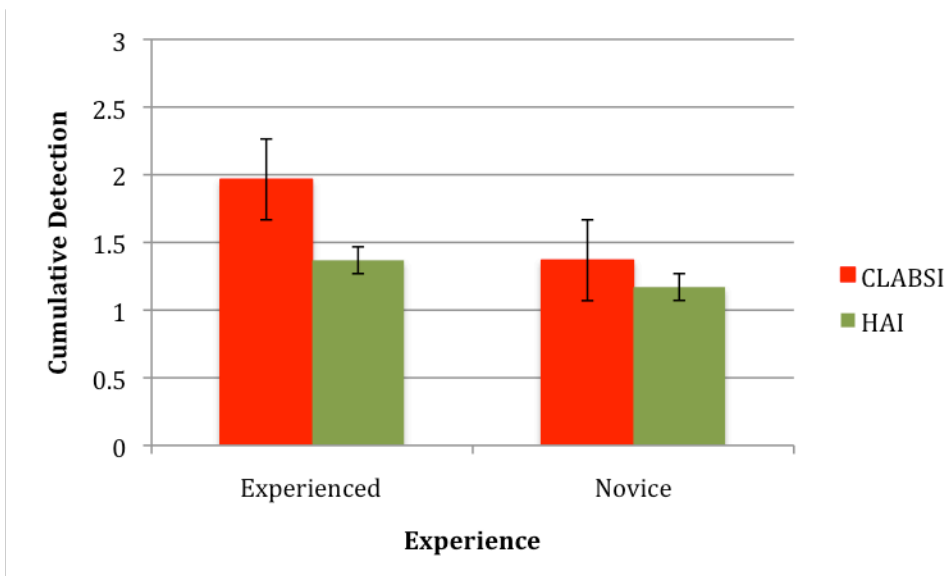

Figure 4. Mean cumulative detection for experience and infection type with standard error bars.

<u>Overall Detection Sensitivity</u>

Generally speaking, these results demonstrate that the procedure employed was sensitive enough to produce variations in problem detection judgments. In addition to demonstrating the success of the methodology, these results suggest that sensitivity varies based on experience, time pressure, risk factors, and infection type. Time pressure appears to play a critical role in detection sensitivity. Time pressure tends to lead to a need for more cues to initiate problem detection, whereas a lack of time pressure allows nurses to evaluate each cue carefully, thus only one risk factor is needed to trigger problem detection. In addition, experience does play a minor role in detection in the sense that experienced nurses were differentially detecting problems based on the type of infection.

Detection Times

Detection time was also used to evaluate problem detection under the assumption that faster detection was associated with superior detection ability.

Time-to-Detect

Detection times were recorded for each response from the time the first cue was presented to the time the nurse selected 'Yes'. Means and standard deviations were calculated for each condition excluding the None category, and are displayed in Appendix E. Mean reaction times were analyzed using a 2(Experience) x 2(Time Pressure) x 2(Risk Factors) x 2(Infection type) split-plot ANOVA. Because there were cases in which the participant did not detect a problem across a particular condition, pairwise deletion was used to account for missing data.

A significant main effect was found for Infection type, $F(1,18) = 6.66$, $p<.05$, $\eta_p^2 =0.291$, such that participants were overall faster at detecting a CLABSI problem compared to other HAI problems (Figure 5). Faster detection for CLABSI may be explained by the possibilities that there are more cases indicating a CLABSI than any other specific HAI, but also that the risk factors indicating a CLABSI may typically be more diagnostic of a CLABSI, such as the patient's central line day.

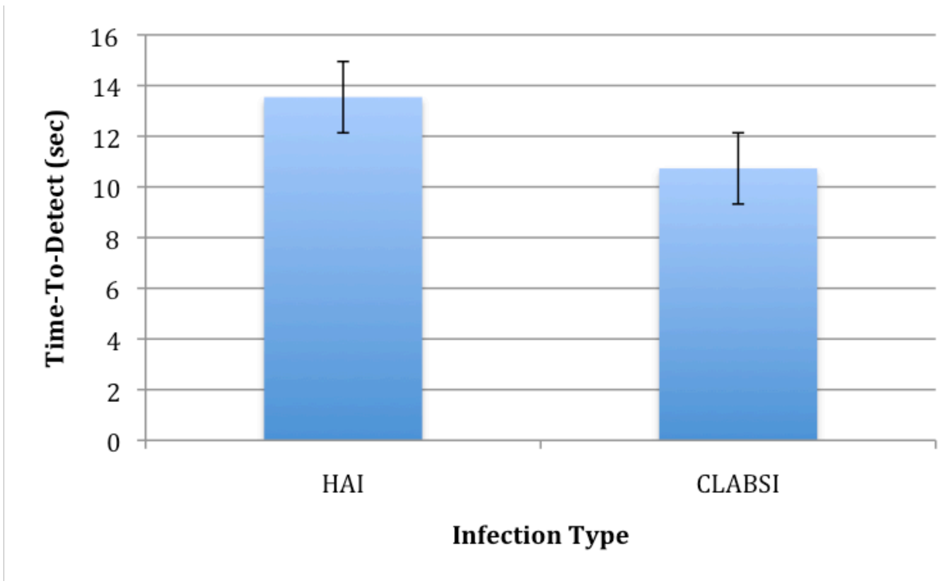

Figure 5. Mean time-to-detect with standard error bars for each infection type.

Risk Factor Encoding Time

A separate analysis was conducted in order to compare how long nurses spent on the risk factors when they were exposed to only one risk factor versus when they were exposed to all three. Is the third risk factor analyzed quickly to confirm an existing position, or is it analyzed as slowly or more slowly, to interpret and integrate it with previous cues? Based on the case study construction, within a family, the identical cue presented in the one risk factor condition was placed third in the three risk factor condition. Thus, time spent on that individual cue could be compared across groups without any impact of the cue's diagnosticity, familiarity, or even sentence length. Mean durations on the one risk factor in the One Risk Factor condition and mean durations on the last risk factor in the Three Risk Factor condition were calculated for each nurse for each case study containing a risk factor. A 2(Experience) x 2(Time Pressure) x 2(Risk Factors) split-plot ANOVA was conducted on those durations. Means and standard deviations are displayed in Appendix E. A significant main effect was found for Time Pressure, such that nurses spent less time on that cue when under time pressure compared to when they were not under time pressure, $F(1,20) = 7.35$, $p<.05$, $\eta_p^2 = 0.269$, which is consistent with the findings from the manipulation check. The main effect of time pressure is displayed in Figure 6.

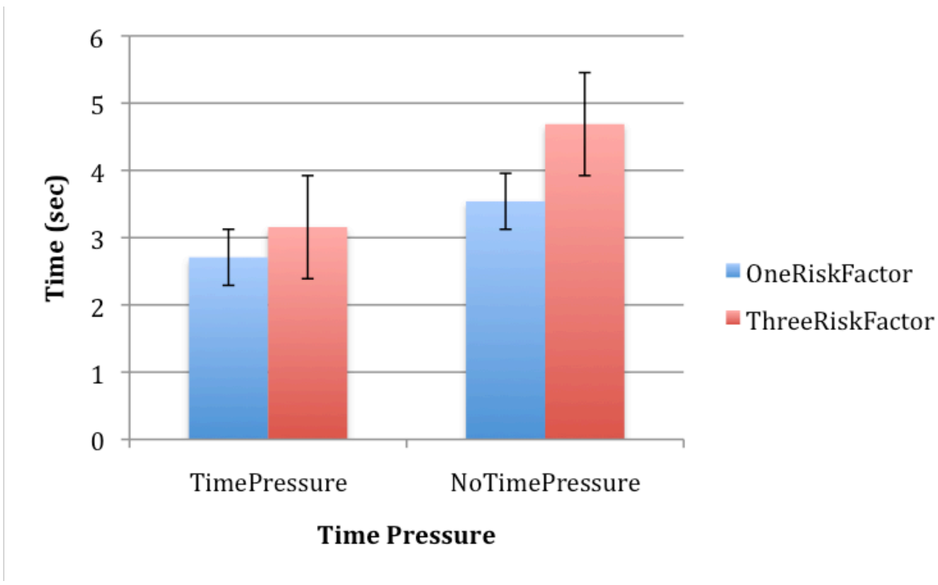

Figure 6. Mean duration on yoked-cue for each level of Risk Factors and Time Pressure.

However, no significant main effect of risk factors was found, such that nurses spent the same amount of time on the yoked risk factor, $F(1, 20) = 3.937$, $p=.061$, $\eta_p^2 = 0.164$. Thus, it can be inferred that encoding the accumulation of three risk factors did not differ from encoding one single risk factor when it comes to time. These results along with the time-to-detect results suggest that speed, unlike sensitivity, did not play a major role in problem detection.

Probability Judgments

In addition to detection sensitivity and speed, nurses were also asked at the end of each case study to report the probability that a patient would develop an infection. These probability judgments were elicited to investigate whether nurses were incorporating the risk factors into their cognitive frames, resulting in higher likelihood assessments. At the end of each case study, participants were asked to judge on a 0-100 scale the probability that the patient would develop an infection. A 2(Experience) x 2(Time Pressure) x 3(Risk Factors: One, Three, and None) mixed ANOVA was conducted on mean probability judgments. Results from the ANOVA are displayed in Table 6, and means and standard deviations are displayed in Appendix E. A significant main effect was found for risk factors as displayed in Figure 7, $F(2,20) = 15.78$, $p<.01$, $\eta_p^2=0.441$. Results are displayed in Figure 7.

Table 6

Significance tests for Probability Judgments.

Variable	F	df	p	η_p^2
Risk Factors	15.78	2, 20	0.000**	0.441
Experience	1.30	1, 20	0.268	0.061
Time Pressure	2.80	1, 20	0.110	0.123
Risk Factors x Experience	2.77	2, 20	0.075	0.122
Risk Factors x Time Pressure	2.12	2, 20	0.133	0.096
Experience x Time Pressure	0.69	2, 20	0.415	0.033
Risk Factors x Experience x Time Pressure	0.81	2, 20	0.452	0.039

A post-hoc analysis was conducted to examine the relationship of the main effect of risk factors. Three pairwise t-tests were conducted to compare each risk factor level with each other, using the Bonferroni procedure to correct for alpha. A significant effect was revealed for both the One Risk Factor versus None condition, $t(23) = 3.597$, $p<.016$, and the Three Risk Factor versus None condition, $t(23) = 5.589$, $p<.016$. However, there was no significant difference found between the One Risk Factor and Three Risk Factor conditions, $t(23) = 1.449$, $p=.161$. Thus, nurses were incorporating the risk factors into their probability judgments, yet the amount of risk factors did not statistically increase nurses' probability.

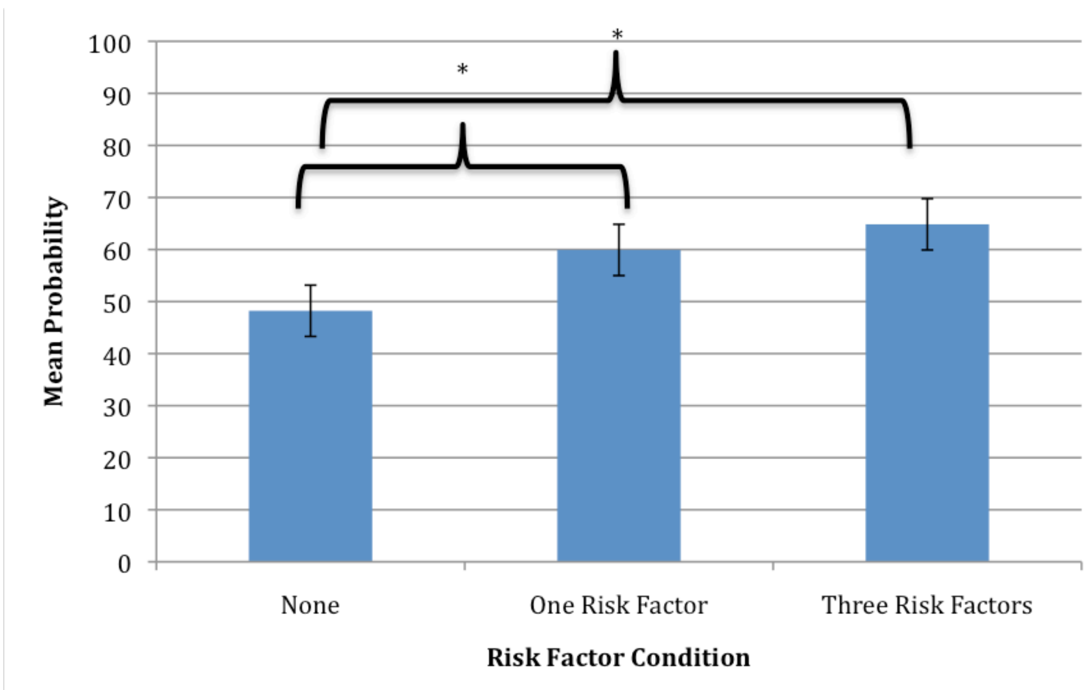

Figure 7. Mean probability judgments for the main effect of risk factor conditions. Significant pairwise t-tests are indicated with brackets and asterisks.

The presence of risk factors did result in a significant increase in nurses' probability judgments, suggesting nurses were in fact incorporating risk factors into their risk assessments. This finding is consistent with the increase in cumulative detection as displayed in Figure 2. However, there was no significant difference found between the one and three risk factor conditions, suggesting that additional risk factors did not significantly affect nurses' probability judgments.

In summary, nurses were able to recognize the risk factors as a signal to a problem, and their ability to recognize the risk factors depended on both experience and time pressure. Nurses were also able to incorporate the risk factors into their probability judgments of the likelihood of developing an infection, yet more risk factors did not statistically increase probability. Thus, the results on problem detection demonstrate that although speed did not produce differential effects, the quality of nurses' detection judgments were meaningful.

Problem Identification

In addition to evaluating problem detection ability, the current experiment also aimed to investigate the relationship between problem detection and problem identification. Thus, problem identification judgments were included in the experiment to see if the nurses actually knew the nature of the problem. Problem identification judgments were first provided at initial detection, and then after every remaining cue until the end of the case study. Problem identification was examined at two points: at the time of detection and at the end of the case study. Nurses either provided a correct identification, incorrect identification, or simply said, 'don't know.' Binary logistic regression was used for both analyses to assess the variables that predicted a correct response. For these analyses, correct identifications were coded as 1, and incorrect and 'don't know' identifications were coded as 0. The None condition was excluded from the following analyses.

An initial analysis was conducted predicting correct identification only at the point of detection with Experience, Time Pressure, Risk Factors, and Infection Type as predictors. The omnibus chi square was not significant, therefore these predictor variables alone were not sufficient for predicting a correct identification at detection, χ^2 (4) = 7.262, p=.123.

A second analysis was then conducted predicting identification at the end of the case study, with Experience, Time Pressure, Risk Factors, Infection Type, and Correct Identification At Detection as predictors. Thus, this analysis was identical to the first, except an additional predictor of correct identification at detection was added. The omnibus chi square was significant, suggesting a sufficient prediction equation, χ^2 (5) = 85.606, p<.01. Nagelkerke's R^2 and -2 log likelihood for this equation was .461 and 194.406 respectively, suggesting moderate variance and fit explained by the model. Results for each predictor in the equation are presented in Table 7.

Table 7

Binary Logistic Regression Results for Each Predictor for Correct Identification.

Predictor	ß	*SE*	Wald	*df*	*p*	Exp (ß)
Experience	.819*	.366	5.997	1	.025	2.267
Time Pressure	-.533	.361	2.174	1	.140	.587
Risk Factors	.364	.361	1.018	1	.313	1.439
Infection	2.209**	.383	33.359	1	.000	9.109
Correct At Detection	2.715**	.479	32.150	1	.000	15.109

Note: * p <.05.
** p<.01

Experience, Infection, and Correct Identification at Detection were all significant predictors of correctly identifying the problem at the end of the case study. Descriptive statistics for each significant predictor are displayed in Table 8.

Table 8

Proportion of correct responses for each significant predictor.

Predictor	Sum[a]	N[b]	Proportion correct[c]
Experience			
Experienced	62	111	0.56
Novice	42	99	0.42
Infection			
HAI	29	104	0.28
CLABSI	75	106	0.71
ID at Detection			
Correct	46	55	0.84
Incorrect	56	147	0.38

[a] Number of cases a correct identification was provided per variable. [b] Total cases an identification was provided per variable. [c] Proportion of total cases correct identification was provided per variable.

Based on the proportion of correct responses for each level of the significant predictors, experienced nurses' problem identifications at the end of the case study were more accurate when compared to those of novices. In addition, nurses were more accurate in identifying a CLABSI infection as compared to another HAI. Again, this finding may be because not only were there more CLABSI cases in the experiment and the operational environment, it can be argued that the risk factors indicating a CLABSI were more diagnostic of a CLABSI compared to the other HAIs. Finally, nurses were more likely to identify the problem correctly at the end of a case study if they correctly identified the problem at detection. This suggests that if nurses accurately detect and identify simultaneously, they are more likely to remain accurate even in the face of new evidence.

Failure to Identify

A separate analysis was conducted to specifically examine the instances in which a nurse provided a 'don't know' problem identification. To determine what variables predicted a failure to identify a problem, binary logistic regression was used. Specifically, 'don't know' responses both at detection and at the end of the case study were coded as '1', and both correct and incorrect problem identifications were coded as '0'. This means that cases were included only if there was an opportunity to identify a problem. The None condition was included in the following analyses.

A first analysis was conducted only examining 'don't know' responses at detection. Experience, Time Pressure, Risk Factors, and Infection Type were included as predictors in the binary logistic regression equation. The omnibus chi square was significant, $\chi^2(4) = 13.775$, $p<.01$, and Nagelkerke's R^2 and -2 log likelihood were 0.060 and 371.960 respectively. Regression results for each variable are displayed in Table 9. Experience was the only significant predictor, such that experienced nurses were more likely to provide a 'don't know' response at detection compared to novices.

Table 9

Binary Logistic Regression Results for Each Predictor for 'Don't Know' at Detection.

Predictor	ß	*SE*	Wald	*df*	*p*	Exp (ß)

Experience	.907**	.263	11.885	1	.001	2.476
Time Pressure	-.002	.252	.000	1	.994	.998
Risk Factors	.093	.224	.174	1	.676	1.098
Infection	.056	.222	.063	1	.802	1.057

Note: * *p* <.05.
** *p*<.01

A second analysis was conducted only examining 'don't know' responses at the end of the case study. For this analysis, Experience, Time Pressure, Risk Factors, Infection Type and whether nurses provided a 'don't know' at detection were included as predictors. The omnibus chi square was also significant, $\chi^2(5) = 76.708$, $p<.01$, with Nagelkerke's R^2 and -2 log likelihood of 0.331 and 253.854 respectively. Thus, the prediction equation examining 'don't know' responses at the end of the case study demonstrated superior fit compared to the prediction equation examining 'don't know' responses at detection. Regression results for each predictor variable are displayed in Table 10.

Table 10

Binary Logistic Regression Results for Each Predictor for 'Don't Know' at the End of the Case Study.

Predictor	ß	*SE*	Wald	*df*	*p*	Exp (ß)
Experience	-.667	.350	3.633	1	.057	.513
Time Pressure	.186	.322	.366	1	.562	1.205
Risk Factors	.672*	.300	5.022	1	.025	1.958
Infection	-.575*	.281	4.023	1	.040	.563
Don't Know at Detection	2.649**	.347	58.227	1	.000	14.134

Note: * *p* <.05.
** *p*<.01

Risk Factors, Infection Type, and if nurses provided a ‘don’t know’ at detection were all significant predictors, yet Experience is no longer a significant predictor at the end of the case study. Descriptive statistics for each significant predictor are displayed in Table 11.

Table 11

Proportion of ‘Don’t Know’ Responses at the End of the Case Study for Each Significant Predictor.

Predictor	Sum[a]	N [b]	Proportion ‘Don’t know’ [c]
Risk Factors			
One Risk Factor	20	90	22.22
Three Risk Factors	23	113	20.35
None	23	80	28.75
Infection			
HAI	29	100	29.0
CLABSI	14	103	13.59
None	23	80	28.75
‘Don’t Know’ At Detection?			
Yes	48	89	53.93
No	18	218	08.25

[a] Number of cases a ‘don’t know’ was provided per variable. [b] Total cases an identification was provided per variable. [c] Proportion of total cases ‘don’t know’ was provided per variable.

Overall, nurses were more likely to provide a ‘don’t know’ at the end of the case study in the None condition compared to the Three Risk Factor and the One Risk Factor condition. Also, nurses were more likely to provide a ‘don’t know’ identification in both the None condition and the HAI condition compared to the CLABSI condition. Finally, nurses were more likely to provide a ‘don’t know’ response at the end of the case study if they provided a ‘don’t know’ response at detection.

Problem Detection Versus Problem Identification

The remaining results aimed to investigate how problem detection and problem identification are related. In the post-study questionnaire, nurses were asked to report both problem detection and problem identification strategies. One particular question asked, "Did you ever find yourself identifying the infection at the same time you decided that the patient was at risk? If so, please indicate how often." Nurses responded by rating on a one to ten scale with 1 rated as 'Never' and 10 rated as 'Every Time'. A second question asked, "Did you ever find yourself deciding the patient was at risk but had not yet identified what was wrong with the patient? If so, please indicate how often." Nurses responded on an identical scale. Responses to these scales were averaged across each between-subject cell. To examine whether nurses reported identifying at detection or identifying after detection was analyzed using a 2(Experience) x 2(Time Pressure) x 2 (Question) mixed ANOVA. There were only two cases where a nurse did not provide a response, thus pairwise deletion was used to account for the missing data. Results revealed a significant main effect of question type $F(1,18) = 4.918$, $p<.05$. Nurses reported problem detection and problem identification as separate behaviors more often than performing the two simultaneously. However, there was no effect of Experience, $F(1,18) = .032$, $p=.860$, nor Time Pressure, $F(1,18) = .127$, $p=.725$. These findings provide further evidence for the face validity of the distinction between detection and identification, such that nurses reported that they treated detection and identification as separate processes when conducting the experiment.

Confidence Judgments

Nurses were prompted to provide confidence judgments in both their detection and identification for each judgment after the nurse detected a problem. If the nurse provided a 'don't know' problem identification, she was instructed to type a confidence of zero. To evaluate nurses' confidence when an actual identification was attempted, problem identification confidence judgments of zero were excluded from this analysis, but are discussed separately.

Confidence judgments were examined both at the point of detection and at the end of each case study. Mean confidence judgments were analyzed using a 2(Experience) x 2(Time Pressure) x2(Position) x 2(Question Type) mixed ANOVA. Means and standard deviations are presented in Appendix E. The Position variable was a within subjects variable with two levels, at the point of detection and at the end of case study. The Question Type variable was also a within subjects variable with two levels. The Question type variable represents the two separate dependent variable measurements, problem detection confidence and problem identification confidence, at both positions. Significance tests are displayed in Table 12. There was one case in which a nurse did not provide any confidence judgments for problem identification at the end of the case study, therefore pairwise deletion was used to account for the missing data.

Table 12

Significance tests for Confidence Scales.

Variable	F	df	p	η_p^2
Position	0.01	1, 19	0.909	0.001
Question Type	0.39	1, 19	0.539	0.020
Experience	0.36	1, 19	0.556	0.019

Table 12 continued

Time Pressure	5.11	1, 19	0.036*	0.212
Position x Question Type	0.73	1, 19	0.404	0.037
Position x Experience	6.89	1, 19	0.017*	0.266
Position x Time Pressure	2.24	1, 19	0.151	0.105
Question Type x Experience	0.12	1, 19	0.729	0.006
Question Type x Time Pressure	0.78	1, 19	0.390	0.039
Experience x Time Pressure	0.35	1, 19	0.562	0.018
Position x Question Type x Experience	4.84	1, 19	0.040*	0.203
Position x Experience x Time Pressure	1.55	1, 19	0.788	0.004
Question Type x Experience x Time Pressure	2.24	1, 19	0.229	0.075
Position x Question Type x Time Pressure	6.31	1, 19	0.021*	0.249
Position x Question Type x Experience x Time Pressure	0.91	1, 19	0.351	0.046

Note: * = $p<.05$
** = $p<.01$
Significant variables are highlighted in bold.

Position, Question Type, and Experience

A significant three-way interaction was found for the effect of Position, Question Type, and Experience, as displayed in Figure 8. Follow-up analyses were conducted to examine the lower order two-way interactions for each Question Type separately. For Problem Detection, a significant two-way interaction was found between Position and Experience, $F(1,22)=5.82$. $p<.05$. However, for Problem Identification, no significant two-way interaction was found between Position and Experience, $F(1,21)=2.72$, $p=0.144$. For problem detection confidence, experienced nurses started off less confident at detection, but became very confident after all information was accumulated. Novice nurses on the other hand, started off very confident at detection, but became significantly less confident after all information was accumulated. Problem identification confidence however, did not vary based on experience or position.

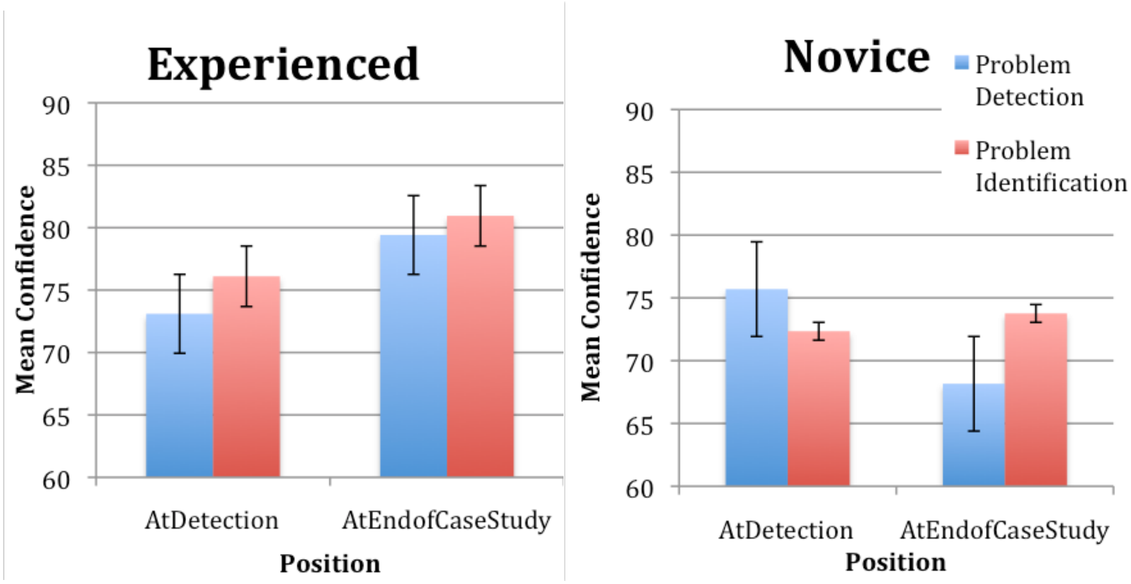

Figure 8. Mean confidence ratings for each level of Position, Question Type, and Experience with standard error bars.

<u>Position, Question Type, and Time Pressure</u>

There were two effects modifying the main effect of Time Pressure. A separate significant three-way interaction was also found for the effect of Position, Question Type, and Time Pressure, as displayed in Figure 9. Post-hoc analyses were conducted to analyze the two-way interactions for each level of Position separately. There was a significant two-way interaction between Time Pressure and Question Type at detection, $F(1,22)=4.63$. $p=.043$, but there was no significant two-way interaction between Time Pressure and Question Type at the end of the case study, $F(1,21)=0.14$. $p=.717$. Overall, detection confidence was substantially higher under time pressure compared to not under time pressure. In terms of problem detection confidence under time pressure, nurses were confident at detection, yet became even more confident at the end of the case study. Thus, not only were nurses more confident while under time pressure, nurses became even more confident in their problem detection judgments after more information had accumulated. On the other hand, problem detection confidence *not* under time pressure resulted in low confidence at detection and even lower confidence at the end of the case study. Thus, nurses were less confident in their problem detection judgments, but became even less confident as more information was accumulated.

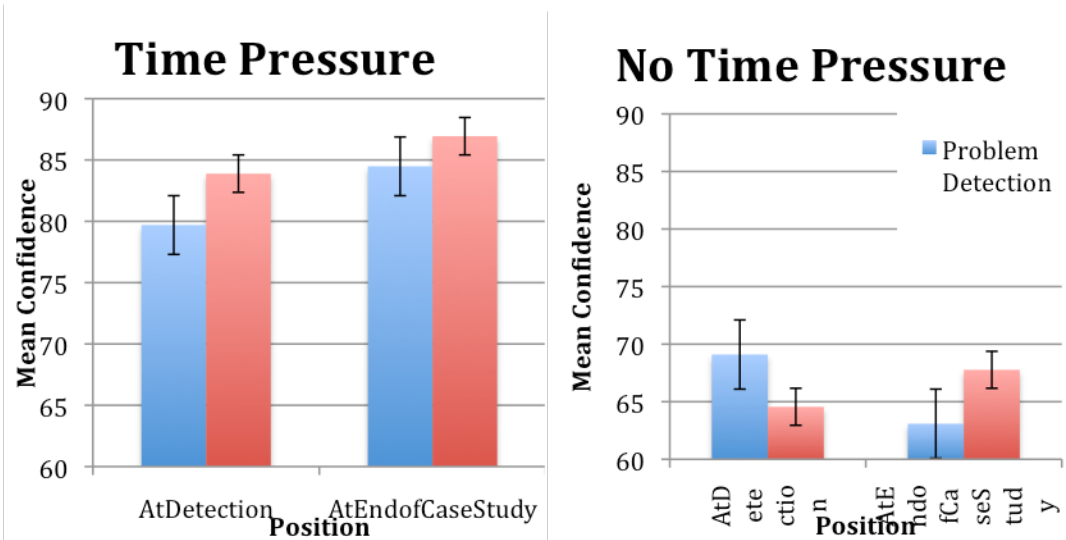

Figure 9. Mean confidence ratings for each level of Position, Question Type, and Time Pressure with standard error bars.

Problem identification confidence did not vary based on position. However, it is interesting to note that for both time pressure and no time pressure conditions, problem detection and problem identification confident at detection varied, yet at the end of the case study, problem detection and problem identification confidence were equal, suggesting detection and identification are treated the same at the end of the case study.

Since nurses reported higher probability judgments in the cases with risk factors compared to none, a similar approach was taken to investigate whether overall confidence was also higher in the cases containing risk factors. A 3-way between-subjects ANOVA was conducted with mean confidence in the One, Three, and None Risk Factor conditions. Results revealed that there was no significant difference in overall confidence between the risk factor conditions, $F(2,40) = 1.04$, $p = 0.363$. Thus, confidence judgments did not follow the overall probability judgments. However, confidence judgments were taken both at the point of detection and at the end of the case study, whereas probability judgments were only taken at the end of the case study.

CHAPTER 4

DISCUSSION

The results of this study provided useful information about the variables that affect problem detection. According to HyGene (Thomas, Dougherty, Sprenger, & Harbison, 2008), people use cues from the environment to generate hypotheses by matching the cues with traces from memory, which then informs decision-making and probability judgments. This process is affected by both task characteristics and cognitive limitations (Thomas, Dougherty, Sprenger, & Harbison, 2008). In the current experiment, nurses had to decide if and when a problem of infection risk was developing, and subsequently make both identification hypotheses and probability judgments. The results of this experiment suggest that both task characteristics (time pressure and risk factors) and cognitive limitations (experience) did in fact affect both detection hypotheses and probability judgments.

Risk Factors, Time Pressure, Infection Type, and Experience

Varying the presence of risk factors affected both problem detection hypotheses and probability judgments. Because the presence of risk factors led to increased cumulative detection compared to cases with no risk factors, it can be argued that the risk factors did in fact serve as diagnostic cues that constrained the number of alternative hypotheses held in the SOC, therefore supporting a problem detection decision. This notion is also supported by the fact that nurses were more likely to attempt problem identification at the end of the case study in cases where risk factors were present. Also, the presence of risk factors led to increased probability judgments at the end of the case study when compared to cases with no risk factors. Again, because the cues were more diagnostic of an infection, the nurse was more likely to have a correct hypothesis and had to consider fewer alternatives, leading to increased probability judgments. It should be noted, however, that confidence judgments were not affected by the amount of risk factors. This is perhaps because nurses may be treating confidence in their decisions differently than the objective likelihood of the patient developing an infection.

Time pressure also played a large role in nurses' detection decisions and judgments. Dougherty and Hunter (2003b) revealed that time pressure led to the generation of fewer hypotheses and increased probability judgments. The results of the current experiment also support these findings. If fewer hypotheses were being generated, the nurses would then have needed more diagnostic information to make a detection decision. In the current experiment, nurses required more cues under time pressure in order to make an affirmative problem detection decision. In addition, nurses' confidence judgments were significantly higher while under time pressure compared to the no time pressure condition. This implies that because there was a constrained number of hypotheses held in the SOC, and these hypotheses were generated with more diagnostic cues, nurses were able to initiate a more refined information search once a detection judgment was made, leading to higher confidence judgments (Dougherty & Hunter, 2003b).

Although this experiment did not originally set out to make predictions about how different infection types affected problem detection, the results revealed some interesting findings. Similar to the introduction of more risk factors, varying the type of infection also seemed to constrain the number of competing hypotheses in the SOC. This notion was primarily supported by nurses' problem identification judgments. Nurses were more likely to both attempt problem identification *and* to provide an accurate identification for cases indicating a CLABSI infection. This finding is probably due to the fact that CLABSI infections are more common at this particular hospital; therefore the nurses have more memory traces associated with this particular infection type, leading to clearer hypotheses concerning the nature of the infection.

Finally, nurses seemed to differ in their detection decisions and judgments based on their relative experience. It can be argued that experienced nurses have more extensive memory traces associated with both detecting and identifying problems with their patients. This implies that experienced nurses should be better able to recognize the cues in the environment and match the cues more closely with memory traces, leading to more accurate hypotheses and judgments. The results of this experiment provided some support for this claim. Experienced nurses were more sensitive to the type of infection compared to novices, suggesting that experienced nurses had more constrained hypotheses in the SOC when making a detection decision.

Furthermore, experienced nurses were also more likely to accurately identify a problem at the end of the case study. Thomas, Dougherty, Sprenger, and Harbison (2008) argue that the hypotheses maintained in the SOC drives the individual to seek further information to hone in on a single hypothesis. This suggests that if experienced nurses did in fact have fewer hypotheses held in the SOC, and thus have fewer competing hypotheses, then they should be more successful in their information search to find the correct hypothesis.

Additionally, experienced nurses were more likely to defer identification at detection. This finding suggests that experienced nurses may be more careful in their detection and identification decisions. Thus, although experienced nurses may have a more refined set of hypotheses held in the SOC at detection, experienced nurses are still more reluctant to provide identification until more diagnostic information is obtained.

This idea is also supported by the nurses' confidence ratings. Experienced nurses' were initially less confident in their decisions and then became more confident as more information accumulated, whereas novice nurses were initially more confident in their decision and became less confident as more information accumulated. This suggests that experienced nurses started off more cautious in their decisions as they were still considering between alternative hypotheses. Once a problem detection decision was made, experienced nurses then searched for cues that would distinguish one hypothesis from another, leading to increased accuracy and confidence.

Detection Vs Identification

The results of this experiment produced some mixed results regarding the relationship between problem detection and problem identification. Based on nurses' reports from the post study questionnaire, nurses treated detection and identification as separate processes. This is mostly consistent with the behavioral data, such that problem detection and problem identification confidence tend to vary based on both experience and time pressure. However, problem detection and problem identification confidence are equal within each experience and time pressure condition. This suggests that by the end of the case study, problem detection and problem identification were treated as the same process. In addition, if can be argued that if the hypotheses held in the SOC drive a detection decision, those hypotheses are then used to guide the nurses' analysis of the subsequent cues to make an identification decision. Thus, nurses treat problem detection as a distinct process from problem identification at the point of detection, but once an initial detection judgment is made; that detection decision is then used to drive identification, combining them into one process.

Application

The results of this experiment can have important implications for the nursing domain and prevention of HAIs. Problem detection sensitivity under time pressure could potentially be impaired if only one risk factor is available, thus could lead to breakdowns in safety. Interventions should be introduced to increase the salience of risk factors in order to overcome the limitation of time pressure. This could be accomplished by designing alerts or warnings, or increase the visual salience of these risk factors both on the patient and on the EHR. In addition, supplemental training on the type of risk factors could also pose a benefit to novice nurses, leading to a closer link between detection and identification.

Limitations and Future Research

Although this experiment has demonstrated promise in both the methodology and results, there are a few limitations that need to be considered. As mentioned previously, years of experience were used as a surrogate for expertise. However, more years of experience do not always equate with expertise. Thus, operationally defining expertise by performance may yield more valid results. Additionally the task was conducted in an online format with one fact presented at a time. In an actual nursing environment, nurses are constantly bombarded with multiple cues and must processes cues all at once. Thus, future experiments could take the information used in this paradigm into a simulated environment to see if detection and identification change. Another limitation of this experiment is the nature of problem detection in the NICU. Because all patients in an ICU are at an increased risk for infection, and neonates are always at an increased risk for infection even if they are considered “healthy”, the nature of the case studies never began as truly neutral. Thus, future studies should apply this experimental paradigm to other domains to see if and how problem detection shifts. Future research should also explore the nuances of what leads to quicker and more accurate identification after detection has occurred. Finally, the current experiment only investigated the effects of three variables on problem detection. This is by no means an exhaustive list of all the factors that affect detection, thus future experiments should incorporate are more complete model.

Nevertheless, the current study supplied important evidence that problem detection is a complex decision process that is dependent on a variety of different factors. The presence of risk factors narrowed the amount of possible hypotheses, leading to increased accuracy and confidence. The presence of time pressure also narrowed the amount of possible hypotheses, leading to an increased reliance on more diagnostic cues and increased confidence. The type of infection also played a role, as more memory traces were associated with CLABSI infections. Experienced nurses also demonstrated more careful consideration of the cues, leading to increased accuracy. Finally, nurses did in fact treat problem detection and problem identification as separate processes, yet these processes were blended together at the end of the case study.

APPENDIX A

PAPER INSTRUCTIONS

General Instructions

- You will be presented with a series of case studies that pertain to individual patients.
- The goal of the experiment is to understand how quickly and accurately nurses decide if there is a problem with a patient, such that an intervention is needed.
- A problem in this sense is defined as “the process by which people first become concerned that events may be taking an unexpected and undesireable direction that potentially requires action” (Klein et al., 2005, p14)
- Case studies will be presented in a format of seven facts presented one at a time.
- A question will appear on the side of the screen that asks if the patient is at an increased risk of infection. It will remain on the screen as you receive new facts.
- You can make your decision at any point during the process.
- Not all patients will necessarily have an increased risk of infection.
- If and when you have decided that:
    - the patient is at risk beyond the level of risk when the patient was first admitted
    - based on the new information action is required

- Select YES as quickly as possible.
- Once the button is selected, you will be asked a few follow-up questions about your choice.

Remember: you can make your decision at any point during the process, and not everyone will have a greater risk of infection than when they entered the hospital.

APPENDIX B

SAMPLE CASE STUDY LAYOUT

In this example, the participant detected the problem after the fifth fact was presented. Risk factors in this example are "Very low birth weight, preterm labor, and PICC line day 21".

Instructions:

You will be presented with a series of seven facts pertaining to an individual patient.

You will receive **new** facts about the patient one at a time, and you can decide when you are ready to receive the next fact.

Your task will be to decide if the patient is at an increased risk for a hospital acquired infection.

Increased risk for infection means:

The patient is at a risk beyond the level of risk when the patient was first admitted

Based on the new information action is required.

If you have decided that the patient is at an increased risk, you should answer yes as quickly as possible.

You can make this decision at any point as you are reviewing the facts.

Note that not all patients will be at an increased risk of developing a hospital acquired infection.

Day of Life 23

Is this patient at risk for infection?

YES CONTINUE

Day of Life 23

Adjusted Gestational Age 35 weeks

Is this patient at risk for infection?

YES **CONTINUE**

Day of Life 23

Adjusted Gestational Age 35 weeks

Very low birth weight

Is this patient at risk for infection?

YES **CONTINUE**

Day of Life 23

Adjusted Gestational Age 35 weeks

Very low birth weight

On NC 2 IL 21-25%

Is this patient at risk for infection?

YES CONTINUE

Day of Life 23

Adjusted Gestational Age 35 weeks

Very low birth weight

On NC 2 IL 21-25%

Preterm labor

Is this patient at risk for infection?

YES CONTINUE

On a scale of 0-100, how confident are you that this patient is at an increased risk for infection?

If you had to guess, what type of infection is this patient at an increased risk of developing? If you are unsure, type “don’t know”.

On a scale of 0-100, how confident are you in your infection identification? If you said ‘don’t know’, type 0.

Day of Life 23
Adjusted Gestational Age 35 weeks
Very low birth weight
On NC 2 IL 21-25%
Preterm labor
PICC line day 21

CONTINUE

On a scale of 0-100, how confident are you that this patient is at an increased risk for infection?

If you had to guess, what type of infection is this patient at an increased risk of developing? If you are unsure, type “don’t know”.

On a scale of 0-100, how confident are you in your infection identification? If you said ‘don’t know’, type 0.

Day of Life 23

Adjusted Gestational Age 35 weeks

Very low birth weight

On NC 2 IL 21-25%

Preterm labor

PICC line day 21

Black male

CONTINUE

On a scale of 0-100, how confident are you that this patient is at an increased risk for infection?

If you had to guess, what type of infection is this patient at an increased risk of developing? If you are unsure, type "don't know".

On a scale of 0-100, how confident are you in your infection identification? If you said 'don't know', type 0.

What is the probability of this patient developing an infection?

APPENDIX C

CASE STUDIES

Case Studies for each condition. Risk factors appear in bold.

Family	Infection	One Risk Factor	Three Risk Factors	None
A	VAP	Day Of Life 21 AGA 26 3/7 **Birth weight 570 g** prolapsed cord Breech apgars 1,6 Female isolette	Day Of Life 21 AGA 26 3/7 **multiple intubations** prolapsed cord **chest tube** **Birth weight 570 g** isolette	Day Of Life 21 AGA 26 3/7 Has primary nurse prolapsed cord Breech apgars 1,6 Female isolette
B	GBS	Term infant now Day Of Life 10 Twin B **Increased episodes of A'sB'sD's** Current weight 3255 g RDS On NcPAP White female	Term infant now Day Of Life 10 Twin B **Foley** **Young maternal age** RDS **Increased episodes of A'sB'sD's** White female	Term infant now Day Of Life 10 Twin B C section Current weight 3255 g RDS On NcPAP White female
C	Staph	Black male Prolapsed cord C section **Day of Life 97** Mom GBS (-) On RA Apgar 0,3,6	Black male Prolapsed cord C section **Birth weight 770g** **15 days PROM** **Day of Life 97** Apgar 0,3,6	Black male Prolapsed cord C section Breech Mom GBS (-) On RA Apgar 0,3,6
D	Enterococcus faecalis	Day of life 95 Triplet C Current weight 2860 g **Birth weight 1150 g** AGA 40 4/7 Cleft lip Abdominal distention with ileus noted on KUB	Day of life 95 Triplet C Current weight 2860 g **Birth GA 27 weeks** **PROM 11 days** **Birth weight 1150 g** Abdominal distention with ileus noted on KUB	Day of life 95 Triplet C Current weight 2860 g Mat transport form Valdosta AGA 40 4/7 Cleft lip Abdominal distention with ileus noted on KUB
E	Staph Epi	AGA 41 4/7 Twin	AGA 41 4/7 Twin	AGA 41 4/7 Twin

		Current weight 3430g **Infant noted to be lethargic** No central access On RA On 45 mL Ng feeds (neosure) nothing by moutn until ST cleared	**Day of life 77** **Infant noted to be lethargic** **Birth GA 30 4/7** **Infant noted to be lethargic** On 45 mL Ng feeds (neosure) nothing by moutn until ST cleared	Current weight 3430g Emergent C section du to breech and transverse presentatior of infant No central access On RA On 45 mL Ng feeds (neosure) nothing by moutn until ST clearec
F	MRSA	Current weight 1600 g AGA 34 weeks **Birth weight 885 g** Transport from outlying facility Apgars 0,1,4,7 On NC 2IL 24% Feeding intolerant	Current weight 1600 g AGA 34 weeks **Increased apnea, brady, desats** **Birth GA 25 3/7** **Birth weight 885 g** On NC 2IL 24% Feeding intolerant	Current weight 1600 g AGA 34 weeks Isolette Transport from outlying facility Apgars 0,1,4,7 On NC 2IL 24% Feeding intolerant
G	Necrotizing enterocolitis	Day of life 13 On NcPAP Spitting **Preterm labor** No IV Full feeds Black female	Day of life 13 On NcPAP Spitting **Extremely low birth weight** **Formula fed** **Preterm labor** Black female	Day of life 13 On NcPAP Spitting Isolette No IV Full feeds Black female
H	UTI	Day of Life 14 Current weight 2235 g **Foley** AGA 36 6/7 On RA No transfusions No IV access	Day of Life 14 Current weight 2235 g **OG NG feeding** **Female** On RA **Foley** No IV access	Day of Life 14 Current weight 2235 g Crib AGA 36 6/7 On RA No transfusions No IV access
I	MRSA	Day of Life 13 AGA 33 4/7 **Erythema left knee** Preterm labor Chronic HTN HELLP syndrome Breast milk OGQ3 hours	Day of Life 13 AGA 33 4/7 **Very low birth weight** **Preterm labor** Erythema left knee **Full enteral feeds** Breast milk OGQ3 hours	Day of Life 13 AGA 33 4/7 Mom pre-eclampsia Preterm labor Chronic HTN HELLP syndrome Breast milk OGQ3 hours

J	CLABSI	Day of Life 5 Current weight 1800 g On HFOV **UAV/UAC access** Oliguria Currently on full feeds and mild hypotension that resolved following further evaluation Isolette	Day of Life 5 Current weight 1800 g On HFOV **Receiving PRBC's x 3, Plts x 2** **Extremely low birth weight** **UAV/UAC access** Isolette	Day of Life 5 Current weight 1800 g On HFOV Has primary nurse Oliguria Currently on full feeds and mild hypotension that resolved following further evaluation Isolette
K	CLABSI	Day of Life 48 AGA 33 weeks **Line day 45** Episodes of apnea/bradycardia Male Isolette	Day of Life 48 AGA 33 weeks **HAI/IL via PICC** **26 week twin** **Line day 45** Isolette	Day of Life 48 AGA 33 weeks Has primary nurse Episodes of apnea/bradycardia Male Isolette
L	CLABSI	Day of Life 69 Birth weight 1820 g Current weight 2790 g **PICC line day 66** AGA 41 2/7 weeks On RA Isolette	Day of Life 69 Birth weight 1820 g Current weight 2790 g **Preterm infant born at 33 weeks gestation** **Receiving long term TPN/IL** **PICC line day 66** Isolette	Day of Life 69 Birth weight 1820 g Current weight 2790 g Has primary nurse AGA 41 2/7 weeks On RA Isolette
M	CLABSI	Day of Life 11 AGA 28 3/7 **PICC line day 11** Current weight 1600g On vent Crib Black female	Day of Life 11 AGA 28 3/7 **Catheter inserted after first week of life** Current weight 1600g **Birth GA 26 6/7** **PICC line day 11** Black female	Day of Life 11 AGA 28 3/7 Resolving Grade II IVH Current weight 1600g On vent Crib Black female
N	CLABSI	Day of Life 15 AGA 25 5/7 **PICC line day 15** White female Eclampsia Oscillator support Increased bradycardia and desats on oscillator	Day of Life 15 AGA 25 5/7 **PROM 72 hours prior to delivery** **Preterm labor** Eclampsia **PICC line day 15** Increased bradycardia and desats on	Day of Life 15 AGA 25 5/7 PICC line day 15 White female Eclampsia Oscillator support Increased bradycardia and desats on oscillato

			oscillator	
O	CLABSI	AGA 30 1/7 weeks Day Of Life 6 **PICC line day 3** No transfusions Murmur present Isolette Has primary nurse	AGA 30 1/7 weeks Day Of Life 6 **Birth GA 29 2/7** **Receiving trophic feeds** **PICC line day 3** Isolette Has primary nurse	AGA 30 1/7 weeks Day Of Life 6 On NcPAP No transfusions Murmur present Isolette Has primary nurse
P	CLABSI	Day of Life 10 C-section due to worsening maternal pre-eclampsia No transfusions **PICC line day 4** NIPPV support Few desats Isolette	Day of Life 10 C-section due to worsening maternal pre-eclampsia No transfusions **Receiving trophic feeds** **Birth GA 29 2/7** **PICC line day 4** Isolette	Day of Life 10 C-section due to worsening maternal pre-eclampsia No transfusions White female NIPPV support Few desats Isolette
Q	CLABSI	Day of life 27 Current weight 1795 g AGA 32 6/7 **Broviac line day 18** Placenta previce-active bleeding On NC 2IL 26% Crib	Day of life 27 Current weight 1795 g AGA 32 6/7 **Receiving multiple transfusions** **On continuous elecare (12cc/hr)** **Broviac line day 18** Crib	Day of life 27 Current weight 1795 g AGA 32 6/7 Has primary nurse Placenta previce-active bleeding On NC 2IL 26% Crib
R		Day of Life 23 AGA 35 weeks **PICC line day 21** On NC 2L 21-25% On NPO Hypothermia Black male	Day of Life 23 AGA 35 weeks **Very low birth weight** On NC 2L 21-25% **Preterm labor** **PICC line day 21** Black male	Day of Life 23 AGA 35 weeks Isolette On NC 2L 21-25% On NPO Hypothermia Black male

APPENDIX D

POST-STUDY QUESTIONNAIRE

Age:

Gender: M F

Experience:

If applicable, how many years have you been in nursing school?

If applicable, how many years have you been working as a floor nurse?

Have you worked in any other unit before this one? If so, please state the other units and for how many years.

Did you have a particular strategy for deciding when the patient was at an increased risk for infection?

__YES
__NO
If YES, please explain:

Did you find yourself selecting "Yes" at the **very first sign** that something with the patient has gone awry? If so, please indicate how frequently you used this strategy.

1	2	3	4	5	6	7	8	9	10
Not at all				Sometimes				Every Time	

Did you find yourself selecting "Yes" after **two or more** facts indicated that something with the patient has gone awry? If so, please indicate how frequently you used this strategy.

1	2	3	4	5	6	7	8	9	10
Not at all				Sometimes				Every Time	

Were there any situations that led you to switch from one strategy to another?

Did you find yourself prolonging selecting "Yes" until you had a better idea what the problem was with the patient? If so, please indicate how frequently you used this strategy.

1 2 3 4 5 6 7 8 9 10
Not at all Sometimes Every Time

Please rank from the following the facts that were the most important in determining that the patient was at risk for infection.
[List of All Risk Factors in Case Studies]

Were there a particular number of facts that you gathered before deciding to select “yes”? If so, how many?
__1 fact
__2 facts
__3 facts
__4 facts
__5 facts
__6 facts
__7 facts
__Other:

Did you ever find yourself identifying the infection **at the same time** you decided that the patient was at risk? If so, please indicate how often.

1 2 3 4 5 6 7 8 9 10
Never Sometimes Every Time

Did you ever find yourself deciding the patient was at risk **but had not yet identified** what was wrong with the patient? If so, please indicate how often.

1 2 3 4 5 6 7 8 9 10
Never Sometimes Every Time

IF selects a 2 or above:
For the instances when you decided that there was a problem with the patient but had not yet identified the problem, what was your strategy for selecting “yes”?
__Immediately select “yes” but delay identification until more information was available
__delay selecting “yes” until more information was gathered
__Immediately select “yes’ and attempt to identify with less confidence
__Other:

APPENDIX E

MEANS AND STANDARD DEVIATIONS

Time Spent on Cues: Manipulation Check

	M (SD)
Time Pressure	3.01 (0.70)
No Time Pressure	4.15 (1.50)

Baseline detection: None only

	Experienced		Novice	
	Time Pressure	No Time Pressure	Time Pressure	No Time Pressure
	M (SD)	*M (SD)*	*M (SD)*	*M (SD)*
Cue				
N1	2.67 (1.75)	1.00 (2.00)	1.17 (1.17)	0.33 (0.52)
N2	3.33 (2.34)	2.00 (2.45)	1.33 (1.34)	1.17 (1.95)
N3	3.33 (2.34)	2.83 (1.84)	1.67 (1.63)	1.17 (1.94)
N4	3.50 (2.07)	3.17 (1.84)	1.83 (1.72)	1.67 (2.25)
N5	4.00 (1.67)	4.00 (1.79)	2.50 (1.87)	2.17 (2.14)

Signal-trial detection

	Experienced		Novice	
	Time Pressure	No Time Pressure	Time Pressure	No Time Pressure
	M (SD)	*M (SD)*	*M (SD)*	*M (SD)*
One Risk Factor				
CLABSI				
Neutral	1.75 (0.94)	1.08 (1.02)	0.83 (1.13)	0.83 (0.68)
Cue	2.17 (0.75)	2.67 (0.81)	1.50 (1.64)	2.50 (0.55)
Other HAI				
Neutral	1.00 (0.89)	0.92 (0.97)	0.50 (1.00)	0.75 (0.27)
Cue	1.17 (0.75)	2.00 (1.27)	1.17 (1.17)	2.00 (0.63)
Three Risk Factors				
CLABSI				
Neutral	1.50 (1.38)	1.33 (1.33)	0.67 (1.21)	0.67 (0.75)

Cue	2.83 (0.41)	2.83 (0.41)	2.00 (1.10)	2.67 (0.52)
Other HAI				
Neutral	0.58 (0.66)	0.83 (1.13)	0.58 (0.66)	0.75 (0.88)
Cue	2.50 (0.55)	2.17 (0.75)	2.17 (0.75)	2.33 (0.52)

Time-To-Detect

	Experienced		Novice	
	Time Pressure	No Time Pressure	Time Pressure	No Time Pressure
	M (SD)	*M (SD)*	*M (SD)*	*M (SD)*
OneRiskFactor				
CLABSI	8.39 (3.87)	11.23 (4.69)	8.66 (3.36)	9.61 (3.69)
OtherHAI	12.63 (9.28)	12.57 (3.13)	13.60 (8.10)	13.98 (6.31)
ThreeRiskFactors				
CLABSI	9.22 (3.91)	10.77 (3.71)	14.61 (14.00)	13.74 (7.33)
OtherHAI	16.94 (7.66)	10.61 (4.03)	13.22 (5.95)	14.11 (5.49)

Cue-Encoding Speed

	Experienced		Novice	
	Time Pressure	No Time Pressure	Time Pressure	No Time Pressure
	M (SD)	*M (SD)*	*M (SD)*	*M (SD)*
RiskFactorCondition				
One	3.33 (0.92)	3.50 (1.80)	2.08 (0.70)	3.59 (1.26)
Three	3.55 (0.84)	4.62 (0.92)	2.76 (1.46)	4.76 (2.66)

Probability Judgments

	Experienced		Novice	
	Time Pressure	No Time Pressure	Time Pressure	No Time Pressure
	M (SD)	*M (SD)*	*M (SD)*	*M (SD)*
Risk Factor Condition				
None	64.86 (29.83)	41.86 (14.37)	45.11 (21.35)	41.08 (30.59)
One	68.44 (21.87)	52.92 (15.67)	58.58 (16.96)	59.72 (17.96)
Three	83.69 (16.17)	61.69 (20.23)	65.69 (24.96)	48.27 (20.93)

Questionnaire

	Experienced		Novice	
	Time Pressure	No Time Pressure	Time Pressure	No Time Pressure
	M (SD)	*M (SD)*	*M (SD)*	*M (SD)*

QuestionType				
IDAtDetection	4.75 (3.30)	5.83 (1.60)	6.17 (1.60)	5.17 (1.60)
NoIDAtDetection	7.75 (2.06)	6.67 (2.07)	6.17 (2.56)	7.83 (1.17)

Confidence Judgments

	Experienced		Novice	
	Time Pressure	No Time Pressure	Time Pressure	No Time Pressure
	M (SD)	*M (SD)*	*M (SD)*	*M (SD)*
At Detection				
Detection	75.65 (23.99)	70.55 (26.99)	83.74 (14.56)	67.65 (21.97)
Identification	83.89 (22.67)	68.31 (25.02)	83.88 (13.85)	60.80 (20.65)
At End of Case Study				
Detection	84.74 (16.46)	74.09 (23.12)	84.23 (13.01)	52.09 (28.02)
Identification	90.41 (14.87)	71.49 (24.36)	83.47 (14.96)	64.05 (17.66)

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