Extending Naturalistic Decision Making to Complex Organizations: A Dynamic Model of Situated Cognition

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Abstract

Naturalistic decision making (NDM) has become established as a methodological and theoretical perspective. It describes how practitioners actually make decisions in complex domains. However, NDM theories tend to focus on the human agents in the system. We extend the NDM perspective to include the technological agents in complex systems and introduce the dynamic model of situated cognition. We describe the general characteristics of NDM and the field of situated cognition, and provide a detailed description of our model. We then apply the model to a recent accident in which a US Navy submarine (USS *Greeneville*) collided with a Japanese fishing vessel (*Ehime Maru*). The discussion of the accident illustrates how decisions made are often a result of the interaction between a variety of technological and human agents and how errors introduced into the complex system can propagate through it in unintended ways. We argue that the dynamic model of situated cognition can be used to describe activities in virtually any complex domain.

Keywords: situated cognition, decision making, process tracing

Since the first naturalistic decision-making conference in Dayton, OH, in September 1989 and the publication of *Decision making in action: Methods and models* in 1993, naturalistic decision making (NDM) has become established as a methodological and theoretical perspective. Because it describes how practitioners actually make decisions in complex domains rather than how they ought to make decisions, many fields of practice have adopted NDM as a doctrinal framework. For example, the US Army has incorporated aspects of NDM in its latest version of *Field manual (FM) 6–0, Mission command: Command and control of army forces* (2003). While NDM represents a major step forward in our understanding of the activities in various fields of practice, the focus of NDM has been on the human agents in complex systems and has not emphasized the influence, contributions, and modeling of the technological aspects of these systems.

The article begins with a discussion of the characteristics inherent in environments in which naturalistic decision making is typically employed. A model of NDM is then described and contrasted with what the authors refer to as the dynamic model of situated cognition (DMSC). The DMSC captures both the human and technological components of complex systems into a single model and illustrates how the decision making of a human is influenced

both by technological agents and other human agents. We use an actual military accident, the collision of the USS *Greeneville* with the *Ehime Maru*, to trace the flow of information through the model, to highlight what decisions were made, how the decisions were made, and how the technological and human aspects of the system contributed to the accident. Thus, the model couples NDM theory with a conceptual model that includes technology to provide a more robust insight into total system performance.

Characteristics of Naturalistic Decision Making

Orasanu and Connolly (1993) describe eight conditions in which naturalistic decision making is typically employed.

- Problems tend to be ill-structured. That is, for some real-world problems, it is not easy or even possible to identify causes and potential courses of actions.
- The conditions are uncertain and dynamic. The situation is continually changing, making it difficult to assess what is happening. Static representations of the system are of little use since the situation is changing so quickly.
- The multiple goals may be ill-defined, may be in conflict, or may shift over time. A military commander might have multiple goals: defeating the enemy, minimizing collateral damage, causing no harm to non-combatants, and protecting soldiers from harm. Not only may these goals change from time to time, they may, in fact, conflict with one another.
- NDM acknowledges the existence of action and feedback loops. Decisions are not discrete events but happen amidst the flow of activity in a system and are impacted by the decisions and activity that precede them.
- Decision makers must respond in real time to changes in the system. Diagnosis of problems and system control often happen simultaneously. Even while a pilot is trying to assess an anomaly or malfunction he or she must still fly the aircraft.
- The domains in which NDM processes are employed often involve high stakes. Examples of these domains include firefighting, military command and control, air traffic control, hospital operating rooms, nuclear power plants, and weather forecasting.
- Multiple players interact in the decision-making process. These players may have either shared or different views of the situation. They must cooperate with one another and update each other in order to perform optimally. While many researchers view these multiple players as humans, the authors of this article agree with other researchers who believe that these players must include both machine and human agents. Interactions between humans and machines are rife in complex systems. These interactions can lead to situation assessments that result in decisions by either the human or the machine. Unfortunately, either the machine or the human may reach an incorrect decision based on the information they receive from another (human or machine) agent.

- NDM typically examines activities that are embedded in organizations. Organizations have their own unique cultures which manifest themselves in accepted norms, policies, guidelines, directives, standard operating procedures, and doctrine. Various aspects of these cultures may be communicated explicitly (verbally or in written documents) or implicitly (through behavioral modeling or system design).

In general, decision-making research has progressed from normative to descriptive to naturalistic. Researchers observed that people often did not make optimal decisions so they began to investigate how and why deviations occurred. While these studies identified several heuristics and biases used by decision makers, their external validity was doubtful because they often used naive participants to perform contrived, discrete tasks. As the eight characteristics above suggest, NDM theories generally describe how decisions are made in operational settings. During the last two decades, NDM research has been conducted in numerous fields of practice, generating a broad empirical base and a variety of theories. Perhaps the best-known naturalistic decision-making theory is Klein's recognition-primed decision model.

A Model of Naturalistic Decision Making

The recognition-primed decision (RPD) model was developed by Klein and his colleagues (Klein et al. 1986) based on their observations of decision makers in operational settings. The model describes how experts use their experiences to arrive at decisions quickly and without the computational (i.e. cost–benefit or utility) analysis of traditional normative decision-making approaches (Raiffa 1968). RPD employs situation assessment to generate a likely course of action and then uses mental simulation to envision and evaluate the course of action. Klein (1993a) described three versions of RPD, which differ in their complexity. In the simplest case, the situation confronting the decision maker is very similar to a situation or a class of situations previously experienced. The decision maker invokes the solution from the previous situation in the present circumstance. In the more complex situation, the decision maker uses mental simulation to envision how the solution might work and what problems might be encountered. If the decision maker envisions a problem, the solution is modified and the mental simulation is repeated with the revised solution. In the most complex situation, an evaluation process determines the solution to be inadequate and the next most appropriate solution must be identified and evaluated. This serial process continues until an adequate solution is found and implemented. According to Klein, a key aspect of all three cases is the process by which the decision maker recognizes the situation.

As a general strategy, RPD appears to be quite robust, having been studied in a wide variety of operational settings. Many researchers have sought to leverage and extend the work already completed on RPD. Klein (1993b) himself proposed consolidating five NDM models into one synthesized model. Some have proposed alternative NDM models (Lipshitz 1993).

Leedom (2003) considered the challenges that arise when RPD is extended to collective decision-making activities in complex organizations. Others have sought to expand on the processes embedded in the model. Noble (1993), for example, further described the process of situation assessment. McLennan and Omodei (1996) proposed a prepriming process which precedes situation assessment and frames that assessment within a particular context. Still others have attempted to build computational models of RPD (Warwick et al. 2002).

We acknowledge the outstanding efforts of all these researchers and believe there is great merit in NDM, in general, and RPD, in particular. We propose to extend the NDM framework into an area which we believe has been somewhat neglected. In general, NDM models do not discuss the technological aspects of complex systems and the influence they have on decision making. We firmly believe that the technological aspects of a complex system should be included in models of naturalistic decision making. Much of what is decided is based on what is perceived by the decision maker. And much of what is perceived is based on the design of the technology in the system. For example, technology can aid or impede decision makers by representing the environment more or less accurately. Decision makers may be passive recipients of data presented by the technology or they may be in a position to shape and direct the technology. In either case, there is an inextricable link between the technological components and the human agents in a complex system. We now describe a conceptual model of situated cognition that incorporates both technological and human aspects of a complex system.

A Dynamic Model of Situated Cognition

Traditional models of cognitive processing and decision making often include modules which represent sensory input, different types of memory, encoding, response selection and execution, and attention (Wickens et al. 2004). Proponents of such models often use controlled laboratory tests to study individuals engaged in activities that focus on selected components of these models. These studies often use college students as participants and involve performing simple tasks for which no experience is necessary. While it is essential that such work be conducted, this type of research neglects the types of cognitive activities that experienced people use in contexts with which they are familiar. Cacciabue and Hollnagel (1995) refer to this level of analysis as 'macrocognition'. Klein et al. (2003) include the following as macrocognitive activities: decision making, uncertainty management, mental simulation, sensemaking, situation awareness, attention management, problem detection, planning, and option generation.

A related field of research, which also values the importance of context and expertise, is referred to as *situated cognition*. Learning theorists combined knowledge from cognitive psychology, sociology, critical psychology, anthropology, and sociocultural theory to investigate the 'fundamental processes of cognition as social and situated activity' (Kirshner and Whitson 1997: 3). Lemke (1997: 38) describes recent research and thought in situated cognition

as the interplay of multiple individuals and their environment. People engaged in normal activities:

'are functioning in microecologies, material environments endowed with cultural meanings; acting and being acted on directly or with the mediation of physical-cultural tools and cultural-material systems of words, signs, and other symbolic values. In these activities, "things" contribute to solutions every bit as much as "minds" do; information and meaning [is] coded into configurations of objects, material constraints, and possible environmental options, as well as verbal routines and formulas or "mental" operations.'

Lemke (1997: 38) further states that

'our activity, our participation, our "cognition" is always bound up with, codependent with, the participation and the activity of [O]thers, be they persons, tools, symbols, processes, or things. How we participate, what practices we come to engage in, is a function of the whole community ecology, or at least of those parts of it we join in with.'

Learning theorists are not the only people who have expressed interest in situated cognition. AI (artificial intelligence) researchers, attempting to model human cognition and build 'intelligent' machines, have seized upon the term. They describe situated cognition as

'the study of how human knowledge develops as a means of coordinating activity *within activity itself*. This means that feedback — occurring internally and with the environment over time — is of paramount importance. Knowledge therefore has a dynamic aspect in both formation and content.' (Clancey 1997: 4)

The AI community emphasizes the importance of feedback and the dynamic nature of the way in which knowledge is formed and utilized.

'In summary, the term *situated cognition* emphasizes that perceptual-motor feedback mechanisms causally relate animal cognition to the environment and action in a way that a mechanism based on logical (descriptive) inference alone does not capture. Embodiment is more than receiving signals from the environment or modifying the environment (such as a process control program in a manufacturing plant). Being situated involves a causal, in-the-moment coupling *within* internal organizing (forming new coordinations) and *between* internal and external organizing (changing stuff in the world). Hence, *new ways of seeing* and *ways of making changes* to the world develop together. Time sensitivity (reactiveness) doesn't mean just reasoning about events — reasoning exists as a physical activity in time (even in the imagination), and *past reasoning experiences* are causally influencing reasoning as it unfolds in time.' (Clancey 1997: 344)

Learning theorists and AI researchers alike understand the role of context in knowledge acquisition. Similarly, their descriptions of situated cognition also include a dynamic environment in which multiple individuals interact with one another and with tools, feedback mechanisms, and the use of previous knowledge to direct behavior and guide the formation of new knowledge. The dynamic model of situated cognition integrates human and machine components and is intended to describe what happens in operational environments with experienced people who are engaged in goal-directed behavior. Thus, their actions and their cognitive processes are situated in a
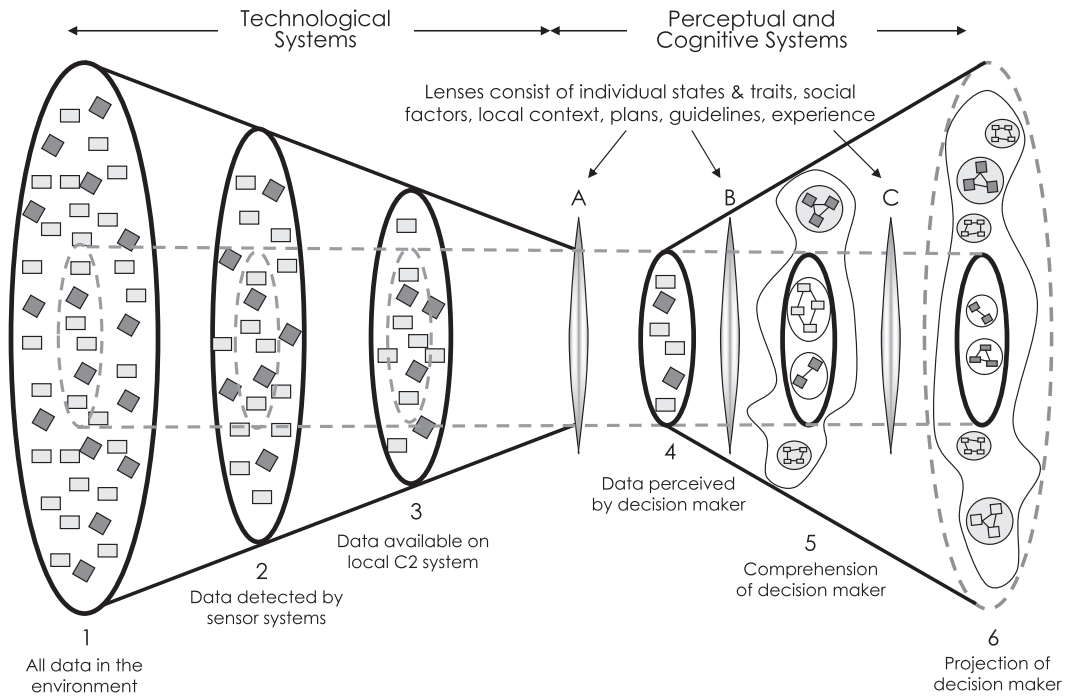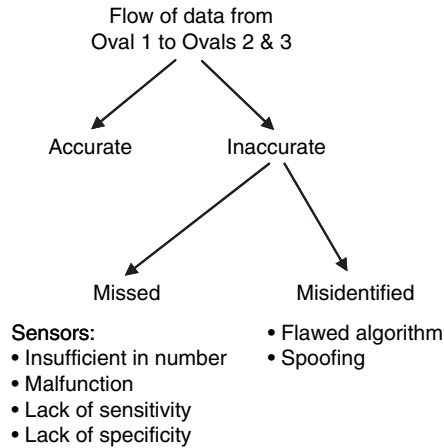
Figure 1. Dynamic Model of Situated Cognition
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particular context. It is assumed that this context is continually evolving (or dynamic) and, therefore, is continually influencing the cognitive activities of the humans in the system. In operational environments, it is often the technological portion of the system that triggers the activity of the human portion of the system.

The dynamic model of situated cognition (Figure 1) emerged as an attempt to illustrate the relationship between technological systems and human perceptual and cognitive processes, which has received only marginal attention in the NDM and the situated cognition literature. The largest oval on the left side of the figure (Oval 1) depicts everything that exists in the environment and may also be referred to as *ground truth* or as a *God's eye view of reality* at that precise moment in time. Oval 1 is a completely accurate picture that is continually being updated and is, therefore, dynamic. In a military C2 scenario, the various shapes represent individual data elements for friendly and enemy entities, friendly and enemy intent, and data on noncombatants, weather, and terrain.

The next oval (Oval 2) illustrates those data elements detected by technological systems. Note that this oval is, in the best of cases, a subset of the first oval. Data elements that are the same in Ovals 1 and 2 represent the accurate detection of items. We refer to this as *technological accuracy*. Not everything in Oval 1 is detected accurately for a variety of reasons (see Figure 2). Sensors

Figure 2.
Problems in Data
Flow from Oval 1

Flow of data from
Oval 1 to Ovals 2 & 3

Accurate   Inaccurate

Missed   Misidentified

Sensors: • Flawed algorithm
• Insufficient in number   • Spoofing
• Malfunction
• Lack of sensitivity
• Lack of specificity

can either miss or misidentify data in Oval 1. Data may be missed for the following reasons:

- There may be an insufficient number of sensors to cover the environment.
- The technology may not be sensitive enough to detect certain classes of data.
- The technology may not have the specificity required to identify certain classes of data.
- Sensors may malfunction.

In Figure 1, Oval 2 includes stars and circles which do not appear in Oval 1. This difference represents the misidentification that can occur as data flow from Oval 1 to Oval 2. Data are misidentified either because the underlying sensor algorithm is flawed or because, as is the case in military environments, the enemy may purposely misrepresent their location and resources in order to deceive friendly commanders. Because the data elements are either missed or somehow misidentified as the data flow from Oval 1 to Oval 2, the resultant inaccuracy may be propagated throughout the rest of the model. And, it may not be apparent to the decision maker what portions of the environment are being detected, what items remain undetected, and what has been erroneously identified. Issues of accuracy and certainty permeate throughout the model and these will be discussed in greater detail later in the paper.

Oval 3 depicts the data displayed on the local decision maker's workstation. These data, again, are potentially an inaccurate and uncertain subset of what is detected by the available technological systems. The inaccuracies and uncertainties introduced in Oval 2 (i.e. the stars and circles) may propagate to Oval 3. In addition, the technology embedded in the local C2 system may misrepresent, through erroneous fusion algorithms, flawed filtering schemes, or poorly designed displays, what is present (i.e. the cross in Oval 3).

In current and planned C2 systems, decision makers are able to tailor their displays to suit their individual preferences. The capability to tailor what is displayed is one way designers may attempt to assist decision makers in

coping with data overload. The drawback in this approach is that it is not always obvious to decision makers which data have been excluded by their preferences. In addition, decision makers may have different preferences selected, resulting in divergent and possibly confusing views of the environment. For example, at a recent military experiment, the automated C2 system generated over 9000 alert messages in a 90-minute period. However, the four participants in the C2 vehicle had tailored their workstations independent of one another. As a result, only a few hundred of the alerts were actually displayed on the workstations; many alerts appeared on multiple workstations while literally thousands of alerts were missed altogether, in some cases depriving the participants of vital information.

The three ovals discussed thus far represent the technological portion of the model. Data displayed on the local C2 workstation are not just a function of how the decision maker has configured the screen; the configuration is also based on how the system designers have constructed the tools employed by the decision maker to cope with data overload. What is displayed on the screen may or may not represent the most important data detected by the sensor array. And since the decision maker's knowledge of the environment is directly related to what is displayed on the workstation, that knowledge may or may not be an accurate reflection of the actual activity in the environment. Further, the sensor array is only a sample or a subset of all the data in the environment. That which is sensed is incomplete and the awareness constructed from it will be incomplete. Incomplete does not necessarily mean inaccurate. If the right data are sampled, the awareness constructed will not be complete but could still be accurate. However, since decision makers usually do not know where the 'holes' are in the friendly and enemy sensor coverage, they are ignorant of how their mental model differs from the actual activities and events of the environment.

Three dynamic lenses are depicted in Figure 1. These lenses, and the role they play in the dynamic model of situated cognition, are somewhat analogous to the lens model developed by Brunswik (1947) and described by Beach (1997). In Brunswik's model, a decision maker must make inferences (Y_s) about events (Y_e) by using available cues (C). The left side of the lens includes descriptions of the events that are occurring in the environment and the cues that represent those events. The right side of the Brunswik's lens describes how the decision maker uses the cues to make inferences about what is happening on the left side of the lens. Hammond modified Brunswik's model to include multiple lenses (Beach 1997). Some decisions might have multiple intermediate decisions that must be reached. In this Brunswikian lens approach, each of these intermediate decisions is represented by its own lens, the output of which feeds forward to the next decision.

The lenses in the dynamic model of situated cognition combine elements from the left side of each lens with informational elements 'resident' in the decision maker and feed forward information or decisions to the next portion of the model. Although the informational elements are the same in each lens, the placement of the lenses in the model suggests that different functions are performed by each lens. As is the case with the human visual lens, perceptual

distortions may result from asymmetries and flaws in the refining process. Lens A, the lens between Ovals 3 and 4, directs attention to selected incoming stimuli. These stimuli are, in most cases, either visual or auditory. Between Ovals 4 and 5 is Lens B, which influences how data are organized into information. The lens between Ovals 5 and 6, Lens C, guides the process of extrapolating current information into predictions about the future.

There are at least six classes of information embedded in the lenses that influence how decision makers perceive, comprehend, and make predictions about activities on the battlefield. *Individual states and traits* represent those relatively enduring (e.g. intelligence or personality) and transient (e.g. fatigue) characteristics of an individual that affect decision making. For a more detailed discussion of human trait and state measurements, see Miller et al. (2003). *Social factors* include issues ranging from small group dynamics to cultural differences that might exist among decision makers. The *local context* influences the data to which a decision maker will attend. The *plan* represents the specific goals to be achieved and the means by which they will be achieved. *Guidelines* represent general procedures to which decision makers may refer if the plan is underspecified. *Experience* refers to previous activities in which a decision maker has engaged. Decision makers rely (either consciously or unconsciously) on prior experiences to influence how they direct their attention. In particular, data which were determined to be useful in previous situations may also prove useful in the current situation. Hence, these data may be valued over other data available to the decision maker. Together, these six classes of information influence what is perceived by the decision maker (Oval 4).

The oval to the immediate right of the first lens (Oval 4) represents all the data actually perceived by the decision maker. The small gray dashed ovals embedded in Ovals 1, 2, and 3 portray the idea that data perceived in Oval 4 are only a portion of data available in previous ovals. Perceived data are a small subset of the data available in the environment, the sensor array, the configuration of the local C2 display, and are based on the characteristics of the lens. The data perceived may be a result of active or passive processes. Active processes refer to data requested or 'pulled' by the decision maker and, therefore, a result of goal-directed behavior. Passive processes refer to data provided or 'pushed' to the decision maker without a request and, therefore, may or may not be relevant to goal accomplishment.

Perceived data are of little value to the decision maker until they are processed further (i.e. comprehended). The term comprehension is used generically in this paper to refer to cognitive processes such as fusion, integration, analysis, explanation, interpretation, and pattern recognition (Endsley 1995). Comprehension is illustrated in Oval 5. The same lens components (i.e. individual states and traits, social factors, local context, plans, guidelines, and experience) that directed attention and led to perception may also influence comprehension. In Oval 5 of the figure, the friendly and enemy icons have been linked and reorganized, suggesting that they have been processed. This oval represents the comprehension of the data elements that were perceived. The oval is embedded in an amorphous shape. This shape suggests that there

are other possible ways the data could be linked and reorganized that would lead to alternative mental representations of the data. The specific comprehension achieved by the decision maker is a function of the data that has propagated through the model and the contents of the lens. The ☺ figure near the bottom of the amorphous shape of Oval 5 represents one possible organizational structure of the friendly data. Note that the configuration of friendly icons (e.g. ⊕) within the oval is not necessarily correct. The ☺ figure may actually be the more veridical comprehension with respect to the environment depicted in Oval 1. The same situation may be true with respect to the configuration of the enemy icons inside and outside Oval 5.

The final oval (Oval 6) represents the projection or prediction of the decision maker. This prediction is based on what has been comprehended by the decision maker (Oval 5) and in the way the decision maker's lens (Lens C) affects that prediction. Alternate views of the battlefield (e.g. ☺) within the amorphous shape but outside of Oval 5 do not contribute to or influence the prediction of the decision maker. As an example, note that the comprehension of the enemy in Oval 5 (e.g. ⌀) has been modified and is shown as ⌀ in Oval 6. Some of the attributes of the enemy that are modified may be location, capabilities, and intentions. Other comprehension elements (e.g. friendly forces, weather, terrain, etc.) are modified according to their own set of criteria. Note that the amorphous shape which surrounds Oval 6 is larger than that which surrounds Oval 5 and contains even more alternatives. This representation depicts the idea that there is much greater uncertainty associated with prediction. Thus, what is actually predicted by the decision maker is only one possible view of the future. The further into the future one attempts to predict, the more uncertain will be the prediction encapsulated in Oval 6.

Situated cognition is not a state that is achieved but a dynamic, ongoing process (Clancy 1997). For example, the sensor coverage and communications network are dynamic. The sensor coverage is shifting constantly as sensors move or fly about the environment, resulting in changes to sensor coverage. These changes in coverage, coupled with possible communications outages, will affect data available in Ovals 2 and 3 and ultimately influence the perception, comprehension, projection, and decision making of the practitioner.

For the sake of simplicity, Figure 1 did not include feedback loops; these feedback loops are included in Figure 3. The feedback loops represent not only the iterative and dynamic nature of the model but also attest to the decisions made by practitioners. These feedback loops also provide insight into the cognitive processing and the decision making of a practitioner. The feedback loops flow from Oval 5 (comprehension) to Ovals 1, 2, 3, and 4 (environment, sensors, C2 workstation, and perception) and from Oval 6 (projection) to Ovals 1, 2, 3, 4, and 5.

The following example illustrates the flow through the model and the role of the feedback loops. There is an enemy unit moving on the battlefield (Oval 1) but it has not yet been detected. At some point, a sensor detects the motion of the enemy unit (Oval 2). Data from the sensor are sent to the friendly unit
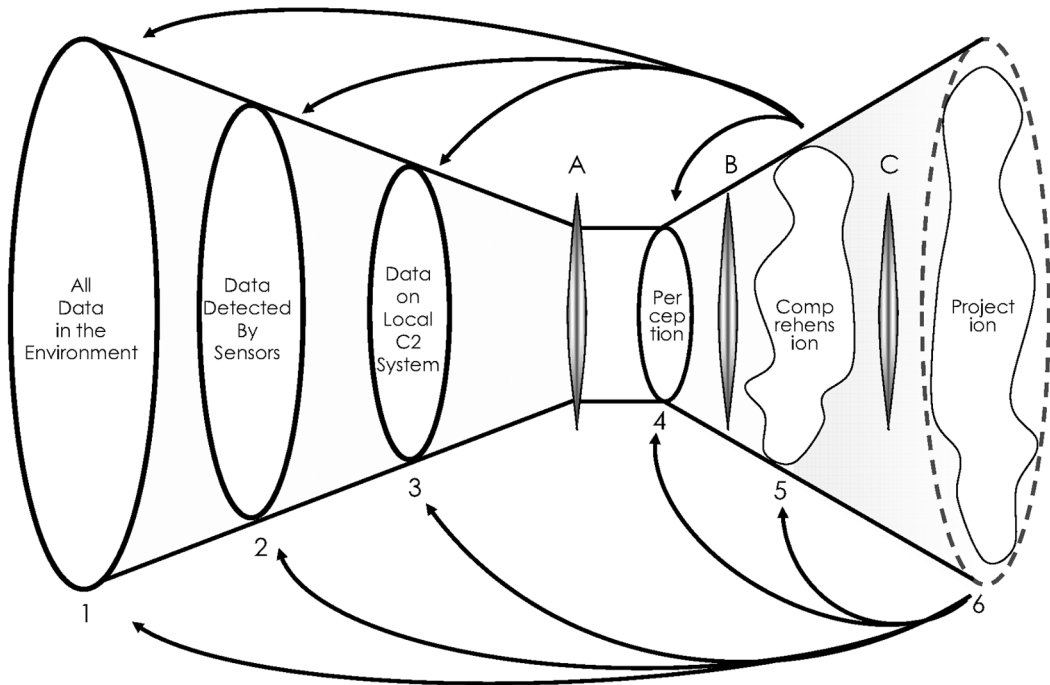
Figure 3. Feedback Loops in the Dynamic Model of Situated Cognition
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and appear on a workstation (Oval 3). If the workstation is configured properly and the decision maker is attending to the workstation (based on contents of Lens A), the data may be perceived (Oval 4). The decision maker may comprehend (Oval 5) there is an enemy of unknown size and strength on the battlefield based on the local context and experience (as well as other contents of the Lens B). Given that comprehension and knowledge of enemy doctrine (as well as other contents of Lens C), the decision maker may expect or project (Oval 6) that the enemy might be of a certain size and moving in a particular direction. Having made that projection, the decision maker may elect to reposition an unmanned aerial vehicle (UAV) to more closely monitor the enemy unit. This decision is represented by the feedback loop from Oval 6 to Oval 2. Once the UAV arrives on station, the sensors on board provide additional data, which flow from Oval 2 to Ovals 3, 4, 5, and 6. The additional data from the UAV sensors will either confirm or correct the earlier comprehension and projection.

There are three other aspects of the dynamic model of situated cognition that have not been fully explained or illustrated thus far. First, there are other feedback loops in the model. These feedback loops extend from Oval 5 (comprehension) to the lenses and from Oval 6 (projection) to the lenses. The rationale for these feedback loops is that the lenses are dynamic; they are constantly changing. The comprehensions, projections, and decisions we make contribute to *the manner in which we view the world*. For example, if

a practitioner believes that there is an enemy unit on the battlefield (Oval 5) then the lens will be focused (and attention will be directed) to look for data that confirm this belief. The lens causes the decision maker to focus on certain data elements (while excluding other data), and the end result is a change in the perceptions, comprehensions, and projections experienced by the decision maker.

The second aspect of the model not yet discussed is the role played by other human agents in the complex system. We believe that input from human agents is injected into the model between Oval 3 and Lens A. The human agent may inject a perception ('Look what just popped up on my radar screen'), a comprehension ('I think there are about 12 tanks out there. It's probably an enemy company'), or a projection ('Looks like they're planning to attack that village'). The lens of the decision maker influences the extent to which input from these other human agents are considered. If the decision maker has found a human agent to be particularly unreliable, then the lens of that decision maker may lean towards filtering out or discounting that agent's input.

The third aspect not fully discussed thus far is the nature of accuracy and uncertainty in the model. Accuracy and uncertainty often interact with one another throughout the model. In an ideal world, data are transmitted from one oval to the next in an accurate manner. However, as suggested earlier, data can be missed or misidentified so that they are no longer veridical with respect to Oval 1. Accuracy (or lack thereof) is a characteristic of both the technological agents and human agents in any complex system and is therefore included in the dynamic model of situated cognition.

Lipshitz and Strauss (1996: 189) characterize uncertainty as 'a sense of doubt that blocks or delays action'. McCloskey (1996) and Klein (1999) list four sources of uncertainty: missing information; unreliable information; ambiguous or conflicting information; and complex information. We believe that uncertainty can be present in the technological portion of the model as well as the perceptual and cognitive portion of the model. For example, technological systems may 'experience' uncertainty and even attempt to reduce uncertainty if data are missing, unreliable, or ambiguous. Present technological systems may be less able to 'cope' with uncertainty (i.e. are more brittle) if the uncertainty is due to conflicting information or the complexity of the information. Humans, on the other hand, have the potential to experience and to cope with all four sources of uncertainty.

The matrix on the left side of the Figure 4 depicts the four possibilities that result when high and low levels of accuracy interact with high and low levels of certainty. Amorphous shapes A–D illustrate four possible comprehensions or projections (Ovals 5 or 6) and the interaction between accuracy and uncertainty. The small white circles in each shape are possible projections whereas the black circle is the most accurate projection (based on the exact contents of Oval 1). The large, off-center oval in A indicates the decision maker is neither accurate nor certain. In B, the decision maker is accurate but still uncertain. In C, the decision maker is very certain, but also highly inaccurate. In D, the decision maker is both accurate and certain. This interaction

Figure 4.
Interaction between
Levels of Accuracy
and Certainty
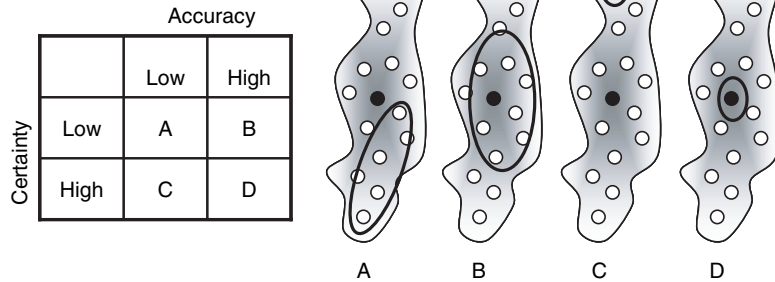
between accuracy and uncertainty occurs throughout the model (i.e. Ovals 1–6). When either accuracy or certainty are low, the data or information that flow on to the next portion of the model will have debilitating consequences on all that follows thereafter. Having described the dynamic model of situated cognition, the next task is to consider a method that can be used to trace the flow of activity through the model.

Applying Process Tracing to the Assessment of Human–System Performance

Technologists and human factors practitioners tend to approach the assessment of human–system performance from different perspectives. Technologists often want to compare the difference between the ground truth or data in the environment (Oval 1) with what the sensor array has detected (Oval 2). At best, this could be described as 'technological performance' but it is not human–system performance. Even a comparison between the data in the environment (Oval 1) and what is displayed on the decision maker's workstation (Oval 3) misses the mark. It is tempting for technologists to make these comparisons because (at least in the case of simulations) the contents of Ovals 1, 2, and 3 can be measured with precision. However, such comparisons do not give an accurate assessment of a decision maker's situated cognition.

In recent years, human factors practitioners have developed a variety of methods to assess situated cognition and situation awareness (see Chipman et al. 2000; Gawron 2000). These methods vary in their degree of subjectivity, rigor, and intrusiveness. Some methods attempt to compare the data in the environment (Oval 1) with the decision maker's perception (Oval 4), comprehension (Oval 5), and projection (Oval 6). These comparisons can result in a more accurate assessment of a decision maker's mental model of the environment than the methods proposed by technologists. However, they are still problematic. They do not describe *how* the decision maker's understanding evolved. They do not account for the technological processes (Ovals 2 and 3) that contribute to situated cognition. Rather than adapting either a technological or a perceptual/cognitive approach to assessing cognition, what

is needed is a human–system performance (HSP) approach. Process tracing is one method that provides such a comprehensive approach to assessing HSP, as well as an approach for assessing situated cognition.

Woods (1993) describes process tracing as follows.

'The goal in these methods is to map out how the incident unfolded including available cues, those cues actually noted by participants, and participants' interpretation in both the immediate and in the larger institutional and professional contexts. This is called a process tracing … method because it focuses on how a given outcome came about.'

In addition, he states, 'The specific techniques within this family are all oriented towards externalizing internal processes or producing external signs that support inferences about internal workings.'

Process tracing involves using multiple data collection methods throughout the human–machine system (Ovals 1 through 6). These data collection methods should be as continuous as possible. Admittedly, this approach is easier to implement during simulations than during free-play field exercises or actual operational settings. However, with recent improvements in data collection techniques and monitoring devices, it is becoming easier to collect continuous data even in operational settings.

Researchers need to know *ground truth* (Oval 1). While in simulations, ground truth can be known in real time. However, in operational settings ground truth can be determined only after the fact and this determination may be imprecise. Researchers also need access to sensor data (Oval 2). These data include where the sensors are located, their operating characteristics (e.g. sensor type, range, etc.), and the data they are collecting. The data detected by the sensor array place an upper limit on human cognition. A decision maker's knowledge of the environment can be no better than what has been detected by the sensors. Investigators should know how the decision makers' local workstations are configured (Oval 3). Further, they need to understand why the decision makers configured the workstations in that way and know what data are (and are not) available to the decision makers because of those configurations. Again, Oval 3 represents a further constraint on human cognition. At any given point in time understanding can be no better than the data the decision makers are able to access.

Data collection in the technological portion of the system (Ovals 1 through 3) involves closely monitoring activities as they unfold and harvesting data from the system after the fact. Researchers can greatly improve the quality of data they will harvest if they work with designers and engineers before the data collection event to ensure that the appropriate activities are recorded and in the correct format and that timing devices are synchronized. Data collection during the perceptual and cognitive portion of the system (Ovals 4 through 6) involves monitoring and measuring the behaviors of the decision makers with as little intrusion as possible.

Researchers must determine the contents of each decision maker's lens. While it may be impossible to correctly assess the entire contents of each individual's lens, the contents can be assessed with tests and interviews before and after the activity being investigated. Eye-tracking technology with gaze

analysis can be used to help determine where decision makers were focusing their attention. Physiological monitoring can identify changes in physiological stress levels of the decision makers. Voice and text transcripts can be used to determine how data were integrated into comprehension and how comprehension led to projections about the future. Activities such as asking decision makers to briefly sketch the most important aspects of the environment they are monitoring can be done quickly with minimal disruption but will provide rich insight into the focus of attention and other thought processes of the decision makers.

These data collection methods, if used to trace the flow of data through the technological and human portions of a system, will not only describe how the decision makers came to understand what was happening in their environment but whether and how that understanding went awry. These methods are consistent with Woods' view of process tracing: 'Process-tracing techniques primarily use data from verbal reports or from records of problem-solver behavior to build protocols that describe the sequence of information flow and knowledge activation' (Woods 1993). Results of this process-tracing method are also useful for informing designers where problems exist in the technological portion of the system.

The next section illustrates the utility of the dynamic model of situated cognition by applying it to the collision between the submarine USS *Greeneville* and the Japanese motor vessel *Ehime Maru* on February 9, 2001. This retrospective analysis traces the flow of data through the technological and human components of the submarine's crew. This case study not only describes what the crewmembers knew but also how the technology prevented them from knowing critical pieces of information. The authors then contrast the analysis of this accident using the DMSC with the analysis that other NDM theories might yield. It is our contention that examining decision making with a model that includes both technological and human components yields a more robust and more accurate explanation of the events.

USS *Greeneville* (SSN 772)

On February 9, 2001, the US Navy submarine USS *Greeneville* collided with the Japanese motor vessel *Ehime Maru* off the coast of Oahu, Hawaii. The submarine was demonstrating an emergency surfacing maneuver for civilian guests onboard for a seven-hour distinguished visitor cruise. As it rose to the surface, the submarine struck the fishing vessel's aft port quarter, causing the ship to sink in less than 10 minutes. Of the 35 Japanese crew, instructors, and students onboard the *Ehime Maru*, 26 were rescued while nine remain unaccounted for, presumed dead.

The problems started when the submarine had fallen behind schedule by 30 minutes and had less than an hour to get to a pre-designated location. There were three surface ships in the vicinity of the submarine. The *Ehime Maru* was closing on the USS *Greeneville* but at this point this information only resided in Oval 1 (ground truth or data in the environment) and in Oval 2 (data detected

by sensors) of the dynamic model of situated cognition. The information on the closing rate of the *Ehime Maru* was not in Oval 3 (data available on the submarine's C2 system) because a critical display system was not working. The analog video signal display unit, located in the control room of the submarine, provides a remote display of sonar data used for surface contact analysis. It was inoperative. Since information on the proximity of the *Ehime Maru* was not available in Oval 3 from the analog video signal display unit, it could not be propagated throughout the rest of the model. At this point, the commanding officer of the USS *Greeneville* made a series of decisions and issued orders that created an artificial sense of urgency in crewmembers in the control room. This elevated time pressure affected the individual lenses (Lens A, B, and C on the right side of the model) of the crewmembers, adversely impacting their ability to accurately process the information residing in Oval 4 through Oval 6 (perception, comprehension, and projection).

One of the decisions made by the commanding officer was to prepare to come to periscope depth. Mandatory procedures for a submarine to come to periscope depth require that the officer of the deck hold a periscope briefing with watchstanders, conduct two good target motion analysis legs of about three minutes on each surface contact, provide the necessary report, and obtain the commanding officer's permission to proceed to periscope depth. These procedures were known to all crewmen (i.e. were part of their lenses). The commanding officer, however, abbreviated these procedures used by the crew to maintain their situation awareness during the periscope depth maneuver. The commanding officer's decision not only compromised the procedures, it virtually assured that the data in the environment (Oval 1) detected by the sensors (Oval 2) would be inaccurate or incomplete. Hence, the data displayed on the C2 workstations (Oval 3) would also be inconsistent with Oval 1; and the perception, comprehension, and projection (Ovals 4, 5, and 6) of the crewmembers with regard to the surface contacts would be formulated based on erroneous data.

Prior to the commanding officer's decision to surface, the sonar technician reported a new contact to the control team. This information from the technician either did not pass through Lens A of the other human agents or was skewed as it passed through. The result was that neither the commanding officer nor the officer of the deck perceived (Oval 4) the situation properly; they did not recognize that the sonar report was information on a new contact. The commanding officer then announced to the control room that he had a good feel for the contact picture and ordered the officer of the deck to proceed to periscope depth on the same course. The officer of the deck was not given enough time to develop an accurate picture of the surface contact situation. He did not conduct the required periscope brief with watchstanders, missing a valuable opportunity to receive and critically assess important contact information from the sonar. He was deprived of input from both the technological agents and the human agents in the system.

Additionally, other crewmembers were not given enough time to do their jobs properly. Upon hearing the sonar technician's report of the new contact, the fire control technician of the watch rushed to complete his analysis of three

surface contacts prior to periscope depth, overlooking an updated 4000-yard closing solution on one of the old contacts (the ill-fated *Ehime Maru*). His focus was entirely on a 'new' contact which he considered to be the primary contact of interest. The fire control technician of the watch's lens was skewed by the false sense of urgency established by the commanding officer which could very well have narrowed the fire control technician of the watch's focus of attention. Further, when the fire control technician of the watch heard the commanding officer say he had a good feel for the contact picture, he assumed the commanding officer was referring to all contacts, including the new one. This provides further evidence of a skewed lens on the part of the fire control technician of the watch, which may have contributed to his decision to remain silent, failing to provide the commanding officer with corrective information.

The commanding officer's erroneous perception led to an incorrect comprehension (Oval 5) of the situation and an inaccurate projection (Oval 6) of where the vessels would be in the future. At no time did the commanding officer discuss the surface picture with the contact management team to verify a common understanding of the surface contacts (Ovals 5 and 6, comprehension and projection). His own situation awareness of contacts was based on two brief walkthroughs of the sonar room and a single review of fire control displays. He was overconfident and pressed for time, and failed to properly use both the technological agents and the human agents in the system to build his understanding of the surface picture. The decision to proceed to periscope depth represents a feedback loop from Oval 6 (projection) to Oval 1 (environment). As the submarine ascended to periscope depth, the contents of Oval 1 were changed and new data were available for propagation through the model.

While at periscope depth, the commanding officer decided to interrupt the officer of the deck's periscope search and performed his own abbreviated visual search for surface contacts. After the periscope searches by the officer of the deck and commanding officer, the fire control technician of the watch cycled back through his surface contacts and correctly calculated a dangerous closing solution for one of the contacts, the *Ehime Maru*. However, the officer of the deck had just stated he had seen no close contacts at periscope depth, and the commanding officer also said he had no visual contacts. These pronouncements so skewed the lens of the fire control technician of the watch that he doubted his comprehension (Oval 5) of the situation (that there was a surface contact in close proximity to the submarine). The fire control technician of the watch's erroneous comprehension generated a decision and a feedback loop from Oval 5 (comprehension) to Oval 3 (C2 workstation). He manually overrode the correct solution presented by his workstation, physically changing the distance of the surface contact (*Ehime Maru*) from 4000 to 9000 yards, reflecting the distance to the visual horizon. The fire control technician of the watch entered this erroneous information into the fire control system. The result of this action was that the speed solution of the surface contact resulted in an impossible speed solution of 99 knots. After the periscope searches, the boat went 'emergency deep', proceeded to 400 feet, and conducted an emergency main ballast tank blow. The ship surfaced underneath the *Ehime Maru*, causing major flooding on that ship, which sank rapidly.

Application of NDM to the USS *Greeneville* Accident

At the beginning of this paper, we described the conditions in which NDM is likely to be employed. These conditions include ill-structured problems, uncertain dynamic environments, ill-defined or shifting goals, action or feedback loops, time stress, high stakes, multiple players, and organizational goals and norms (Orasanu and Connolly 1993). All of these conditions were present on the USS *Greeneville*. Given the presence of these conditions, it is appropriate to consider how our extension of NDM, which addresses cognition of multiple agents in a complex system, compares with present NDM models.

   We submit that the dynamic model of situated cognition has advantages over current NDM models in at least four areas.

1   *Technological aspects of complex systems*. When the dynamic model of situated cognition is used to describe the events which took place on the USS *Greeneville*, it is clear that the accident is a result not only of decisions made by human agents but also of the data that flowed through the technological agents to the human agents in the complex system. Current NDM models discuss the 'environment' but none really acknowledge the tight coupling of the technological and human agents in complex systems. In the USS *Greeneville* accident, NDM models might begin the analysis by considering what data were available to the human rather than what data resided in the system.

2   *Data flow*. The dynamic model of situated cognition depicts the flow of data from the external environment through the technological agents to the human agents. The model makes it apparent where data have been blocked, missed, or altered as they propagate through the system. NDM models are excellent for describing how a practitioner arrived at a decision in complex system based on the data available. In the USS *Greeneville*, NDM models would typically start with the data that were available on the crew workstations (Oval 3). However, whether designing a complex system or investigating a mishap in a complex system, it is necessary to be cognizant of what could have been known and what should have been known by both the technological and human agents throughout the entire system.

3   *Multiple players*. Although the conditions in which NDM is likely to be employed normally include multiple players, many NDM models describe the activities of a single decision maker. In general, NDM models are able to describe the decisions made by the commanding officer or the officer of the deck but are less able to describe the interactions among multiple practitioners and the decisions they make. The dynamic model of situated cognition takes into account the fact that there are multiple human and machine agents in a complex system and that these agents interact with one another in ways which affect the decision-making process.

4   *Dynamic nature of decision makers*. NDM models consider the role of expertise. In Klein's RPD model, greater expertise results in the decision maker having experienced a greater number of similar instances with which to compare the current situation. In general, however, current NDM

models do not adequately address individual states and traits or social factors. Aboard the USS *Greeneville*, although the commanding officer was an experienced decision maker, he was probably stressed from being behind schedule and from his desire to impress the distinguished visitors. He communicated a sense of urgency to his crew with his decisions and his actions. The dynamic model of situated cognition takes such factors into account. The contents of the lenses include experience, social factors, individual states and traits, the local context, specific plans, and broad guidelines. These elements permit analysis of decisions based on both transient individual and situational characteristics as well as enduring individual and organizational characteristics.

Conclusion

We believe the dynamic model of situated cognition extends current NDM models in a significant manner — by fully considering the technological portion of a complex system. The model we propose offers an innovative way to view complex systems in which humans and machines function as cooperative agents. The dynamic model of situated cognition recognizes the unique contributions made by both the technology and humans. By employing process-tracing methods to track the flow of data through the model, it is easy to determine where the data may have been blocked, how lenses may have been skewed, and how human agents arrived at erroneous perceptions, comprehensions, and projections, which then resulted in poor decisions.

We have used this model previously to describe events in numerous complex systems. However, the model might also be used in a predictive manner. For example, the model could be used to guide system development. Designers who want to maximize system performance need to consider both sides of the model. They need to ensure sufficient sensors are available to detect data in the environment. Data from the sensors need to be relayed to the C2 workstations and displayed on the workstations in a manner that will not overload decision makers. And decision makers need to be aided so that their perceptions, comprehensions, projections, and decisions facilitate the accomplishment of the system's goals.

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