Modeling the Dynamics of Time-pressured Diagnostic Sensemaking:

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Abstract

Building on an in-depth study of clinical problem solving in crisis situations, we develop a formal mathematical model of diagnostic sensemaking that represents the interactions among acting, interpreting cues, and cultivating new diagnoses. Driven by powerful reinforcing dynamics, the interplay among these processes opens and closes windows of opportunity for adaptive sensemaking. There are critical moments before which each activity can remediate weaknesses in the others, and critical moments beyond which the inertia of a dysfunctional sensemaking activity can no longer be deflected.

INTRODUCTION

Understanding and improving action-oriented sensemaking during crises in complex, high-stakes settings such as medicine, aviation, nuclear power, or fire-fighting is a crucial aspect of organizing for high reliability. When facing a complex and ambiguous situation where quick action is needed, people have to make sense, to create meaning that will allow them to act. To act, people need to be able to answer the question, what is happening here? Diagnostic problem solving in complex, high-stakes settings is not a situation where "meaning already exists and is waiting to be found." Rather it "awaits construction that might not happen or might go awry…" (Weick, 1995a: 15). Generating a plausible story or explanation about ambiguous cues helps organize and launch action; cues generated by acting help people know what further action routines or rethinking may be needed. Given plausible stories or diagnoses about what is happening, do people then exploit known procedures to address the problem or do they reinterpret the situation by exploring additional diagnoses (cf. March, 1991)? The interplay between these processes under time-pressure (Rudolph and Repenning, 2002) can make the difference between success and failure, even life or death.

In this paper we explore how people address an unexpected and ambiguous problem with dire consequences by taking action, interpreting cues revealed by that action, revising their current view of the situation, and recursively taking more action. Our theory development process starts with two premises. First, research on sensemaking shows that "when action is the central focus, interpretation, not choice, is the core phenomenon" (Snook, 2000; Weick, Sutcliffe, & Obstfeld, 2005: 409). Rather than conceptualizing people as decision-makers evaluating and choosing among options whose meaning is somehow pre-constituted, we see them engaged in a meaning making process in which their own existing frames or diagnoses shape and are shaped by how cues are interpreted (Bartunek, 1984; Klein, Phillips, Rall, & Peluso, 2006; Steinbruner, 1974; Weick, 1987). Second, diagnostic problem solving does not rely solely on stand-alone, discrete episodes of judgment and choice, but rather is a continuous process involving feedback (Hogarth, 1981; Kleinmuntz, 1985; Weick et al., 2005). Discrete decisions without feedback have been likened to hitting a target from a distance in one try; it is much easier when one can monitor and correct the trajectory based on feedback (Hogarth, 1981; Kleinmuntz, 1985). When feedback is available, the focus shifts away from each individual choice or decision to a larger meaning making process in which numerous instances of noticing, bracketing, interpreting, and acting accrue in a current view of the situation and ideas about how to take action. Our modeling effort focuses on diagnostic sensemaking as a dynamic process in which problem solvers revise and redraft their diagnoses as they go (Kleinmuntz, 1985; Hogarth, 1981; Weick et al. 2005).

Our goal in this paper is to enhance theory about this recursive sensemaking by clarifying the dynamic relationships among three processes: 1) acting, 2) interpreting, and 3) cultivating new diagnoses. We first summarize key concepts from the sensemaking literature, then situate sensemaking in the specific context of medical diagnoses, and finally describe our approach to articulating and extending sensemaking theory based on computer simulation.

Sensemaking

"Sensemaking is about the interplay of action and interpretation rather than the influence of evaluation on choice" (Weick et al., 2005: 409). Sensemaking is a process by which people select out or bracket cues in the constant stream of experience to create a "situation that is comprehended explicitly in words and that serves as a springboard into action" (Taylor & Van Every, 2000: 40). Sensemaking is an ongoing process that recursively links action, attention to cues generated by action, and interpretation of those cues.

One of the important elements of the diagnostic process suggested by the sensemaking paradigm is the role of plausible stories or diagnoses in facilitating action (Gephart, Steier, & Lawrence, 1992; Gioia, 1986; Snook, 2000; Weick, 1993b; Weick, 1995a; Weick et al., 2005). To take action, people formulate plausible accounts of what is happening (Gephart et al., 1992; Gioia, 1986; Klein et al., 2006; Snook, 2000; Weick, 1993b; Weick, 1995a; Weick et al., 2005). As long as these stories are sufficiently plausible, they provide a launching pad for action:

> The important message is that if plausible stories keep things moving, they are salutary. Action-taking generates new data and creates opportunities for dialogue, bargaining, negotiation, and persuasion that enriches the sense of what is going on. (Weick et al., 2005: 409)

Plausible stories are the starting point for action that allows people to

> [create] truths of the moment that change, develop, and take shape through time. It is these changes through time that progressively reveal that a seemingly correct action "back then" is becoming an incorrect action "now." (Weick et al., 2005: 412-413)

Sensemaking theory has taken an optimistic view of how plausible stories, including diagnoses, help problem solvers move closer, through successive approximations, to a diagnosis of a problem that is adequate to launch effective action. The sensemaking literature has not, however, explicitly captured the dynamics by which such updating occurs. Sensemaking theory relies on the assumption that the sensemaking process automatically generates mid-course corrections.

Fixation on a Diagnosis

However, there is ample evidence in studies of "fixation error"—a process in which a person sticks with early-developed meanings despite countervailing external cues—that such mid-course corrections often do not happen. A plausible but incorrect story persists as sensemaking filters and even distorts cues from the environment to prevent revision of the story (Cook & McDonald, 1988; De Keyser & Woods, 1990; Elstein, Shulman, & Sprafka, 1978; Finkelstein, 2003; Johnson, Moen, & Thompson, 1988; Johnson & Thompson, 1981; Smith & Blankenship, 1991; Voytovich, Rippey, & Suffredini, 1985; Xiao & MacKenzie, 1995).

For example, Captain Rogers of the U.S.S. Vincennes believed evidence that a hostile Iranian fighter plane was headed his way but his crew mistakenly shot down a commercial Iranian airliner (Cannon-Bowers & Salas, 1998; Roberts & Dotterway, 1995). In 1994, American F-15 pilots in Iraq had visual, auditory, and tactical information that suggested a hostile Iraqi Hind helicopter, but they shot down an American Black Hawk helicopter (Snook, 2000). Smoke jumpers had many times before managed ravine fires successfully and believed they would do the same in Mann Gulch, Montana in 1949, but 13 died when they could not drop their tools or accept orders to take refuge in an escape fire (Weick, 1993b).

In each of these events people launched into action with the aid of highly or moderately plausible diagnoses of the situation but failed to revise these diagnoses in a way that improved their fit with reality. Sticking with the current (faulty) view, a failure to improve the fit with external reality has been called a "collapse" of sensemaking (Weick, 1993b). Rather than seeing these failures to revise as a collapse of sensemaking, we follow Snook (2000) in emphasizing that people were still actively making sense of these situations. They took action, interpreted cues stirred up by this action, elaborated a plausible diagnosis, and continued to interact with the environment that their sensemaking allowed them to perceive. In each case, early-generated stories in the sensemaking process were plausible and were updated through interpretation of external cues produced by their actions, yet these updates somehow diverged from crucial aspects of external reality in a way that led to disaster (cf. Snook, 2000). Sensemaking did not stop, but rather, people continued making sense of the stream of experience with some distortion or limitation of their data gathering and story updating that foiled effective action.

Modeling the Process of Diagnostic Sensemaking

Addressing acute medical problems is the kind of complex, ambiguous, often high-stakes situation that puts tough demands on sensemaking. These crisis situations are challenging because people confront a combination of handling novel demands that require skillful exploration or reconsideration of ambiguous cues and handling many routine demands that require efficient exploitation of known procedures (Rudolph and Repenning, 2002). An unfamiliar or novel presentation of a problem must be diagnosed and, at the same time, standard operating procedures need to be executed quickly. This requires a delicate balance of acting, interpreting, and rethinking.

Our theory development process began with data from an in-depth observational study of diagnostic problem solving by 39 doctors facing a simulated[1] acute care crisis in a high-

[1] We use the term "simulation" in two ways in this paper. The first use refers to the initial source data for the study. These data were provided by a full-field, high-fidelity simulation (i.e. the research participant is in a fully equipped and staffed Operating Room (OR) with a computer controlled mannequin patient). The second use of the term refers to the computer-based simulation we conducted to analyze the behavior of our mathematical model.

fidelity simulated operating room crises (Rudolph, 2003; Rudolph & Raemer, 2004). Drawing on theory and data from other studies of diagnostic or crisis problem solving under time pressure (Cohen, Freeman, & Wolf, 1996; Cook et al., 1988; Cook & Woods, 1994; De Keyser et al., 1990; Dörner, 1997; Elstein et al., 1978; Johnson, Hassenbrock, Duran, & Moller, 1982; Xiao et al., 1995) and sensemaking theory (Gioia, 1986; Schwandt, 2005; Snook, 2000; Weick, 1993b; Weick, 1995a; Weick et al., 2005), we developed a detailed dynamic model of a clinician attempting to diagnose and resolve a challenging problem to preserve the health and life of the patient. Although many theoretical principles and empirical results are relevant to this model, creating a viable working model requires articulating these bits and pieces and filling many gaps. Through an iterative model building and simulation process, we induce an internally consistent theory (represented by our model) of the mechanisms by which people blend acting, interpreting cues, and cultivating diagnoses. This conversation between dynamic model and empirical content provides insights into theory and practice.

METHODS

To clarify the interplay of action, interpretation, and rethinking in sensemaking, we developed a mathematical model that can be simulated by computer. Rather than deduce our model from general principles, we used the methods of grounded theory to build our model from fragmentary existing theory and data from Rudolph's in-depth study of diagnostic problem solving. Through an iterative process of theory elaboration (Vaughan, 1992), we refined the model through constant comparison between our emerging theory (represented by our formal model), other studies of diagnostic problem solving, and related literature on sensemaking. While grounded theory is most commonly used to build theory from raw data using qualitative analysis, the method is not restricted to this application (Suddaby, 2006). Strauss and Corbin (1994) were proponents of developing formal (or general) theories grounded in previously generated domain-specific analyses and point out that other proponents not only advocated using grounded theory with quantitative (not just qualitative) analysis, but also suggested using it to generate theory from theory (Glaser & Strauss, 1967).

We chose formal modeling as a tool for enriching theory on diagnostic sensemaking for two reasons. First, while the sensemaking literature clearly addresses the interplay of action, interpretation of cues, and redrafting of one's current view or diagnosis (Weick et al., 2005: p. 409), the dynamic interplay of these processes is much less clear. Since these processes are hard to study naturalistically, modeling provides a way to synthesize findings from a range of studies to illuminate the interplay. Second, despite the great variety of studies invoking the sensemaking paradigm, these many different analyses converge in describing an inherently dynamic process. Theorizing about dynamic processes without formal models is notoriously error-prone and can lead to important logical gaps and inconsistencies (Sastry, 1997; Sterman, 1994). Inducing a formal mathematical model from existing data and theory provides an approach for both identifying structures common to the different narratives and for enforcing the internal consistency of the emerging theory (Black, Carlile, & Repenning, 2004; Rudolph & Repenning, 2002; Sastry, 1997; Sterman & Wittenberg, 1999). Translating a narrative theory into a mathematical model dilutes some of the richness and nuance of the original. The benefit, however, is an internally and dynamically consistent theory whose central structures and relationships are explicitly, rather than implicitly, represented.

The origin of our theory was Rudolph's in-depth analysis of diagnostic problem solving in operating room crises (Rudolph, 2003; Rudolph et al., 2004). Following established procedures for grounded theory building (Strauss et al., 1994; Suddaby, 2006), we used Rudolph's typology of four diagnostic problem solving modes as our source data. We started the theory building process by translating her text-based constructs and theoretical relationships into the system dynamics language of stocks, flows, and feedback loops (Forrester, 1961; Sterman, 2000). To construct the model (which represents our theory) we used a process of constant comparison between our diagrams and the constructs and relationships identified in Rudolph's study, and in other studies of diagnostic sensemaking and problem solving (Cohen et al., 1996; Cook et al., 1988; De Keyser et al., 1990; Elstein et al., 1978; Johnson et al., 1982; Johnson et al., 1988; Klayman, 1988; Klayman & Ha, 1987; Klein et al., 2006; Klein, Pliske, Crandall, & Woods, 2005; Klein, Orasanu, Calderwood, & Zsambok, 1993; Weick et al., 2005; Xiao et al., 1995). Through this processes of iterative model elaboration and revision, we translated the emerging set of relationships into a formal mathematical model and then used computer simulation to analyze it. Lastly, we returned to the Rudolph's empirical data as well as the literatures on sensemaking and diagnostic problem solving, noting both similarities and differences. The result is a theory that addresses gaps in the sensemaking literature by clarifying how action, interpretation of cues, and cultivating new diagnoses interact.

FOUR MODES OF DIAGNOSTIC SENSEMAKING: EMPIRICAL SOURCE DATA

To ground the mathematical model in concrete data, we begin by describing the diagnostic challenge and findings that served as the basis of our grounded theory building (Rudolph, 2003; Rudolph et al., 2004). Rudolph's study examined diagnostic problem solving by 39 doctors in a simulated acute care crisis.   The doctors were advanced anesthesia residents at several teaching hospitals taking part in required simulator-based training.

The clinical problem. In the simulation scenario studied, the anesthesiologist is called to take over anesthesia in an operating room where a 29-year-old woman urgently needs an appendectomy. The scenario presents a common, but serious problem in anesthesia: difficulty with the process of ventilating, that is, breathing for the patient using a mechanical bellows. A variety of diagnoses for the ventilation problem are plausible, but contradictory evidence is present for each, except one: The patient has exhaled some mucous into the tube, partially blocking it. Some air can get through the tube, but not enough for the patient to survive. This is the actual cause of the problem. Treatments addressing diagnoses other than the mucous plug in the breathing tube will not result in any sustained improvement in the patient's status. With a slowly dwindling level of oxygen in her blood, the patient can have uneven heartbeat and even go into cardiac arrest if the problem is not rectified. The "stream of experience" doctors face in this situation includes the clinical signs and symptoms indicating the patient's status. First line treatments and diagnostic tests produce additional cues.

Sensemaking modes. Rudolph inductively classified doctors' verbal statements and clinical actions into four different sensemaking modes in addressing this diagnostic challenge: "stalled," "fixated," "vagabonding," and "adaptive." The *stalled* problem solvers had difficulty generating a plausible diagnostic story to launch themselves into action. Studying the clinical signs associated with the ventilation problem, they apparently couldn't assemble them into a coherent diagnosis and, lacking this, couldn't confidently exploit known treatment and test algorithms for any given diagnosis. Since they didn't take therapeutic action or conduct diagnostic tests, they did not generate new data to inform the process of generating diagnoses and were unable to resolve the ventilation problem.

In contrast, those in the *fixated* sensemaking mode quickly established a plausible diagnostic story to explain the ventilation problem to themselves. This plausible diagnosis served as a launching pad for pursuing known algorithms for treatments and tests. Most fixated clinicians exploited a single known treatment over and over (rather than advancing through a variety of steps in a treatment algorithm). While fixated problem solvers quickly and confidently generated an initial diagnosis, and cursorily explored one or two others, they returned over and over to the initial leading diagnosis as the main way to view the situation. Working with this plausible (but erroneous) diagnosis, they gradually established a self-fulfilling process in which they interpreted the feedback they got as increasing the plausibility of that story. Because the fit of their leading diagnosis with external reality did not improve, they did not address the underlying problem of the blocked breathing tube.

Although previous studies of fixation error (also known as premature closure or tunnel vision) generally concluded that broadening the range of alternatives considered is the needed antidote (Gaba, 1989; Johnson et al., 1982), Rudolph found a sensemaking mode she labeled diagnostic *vagabonding*[2] in which doctors generated a wide range of plausible diagnoses, but utilized very few steps of standard algorithms for addressing these

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[2] This follows work of Dietrich Dörner, who identified a similar phenomenon among public officials attempting to identify effective strategies for public policy (Dörner, D. 1997. ***The Logic of Failure: Recognizing and avoiding error in complex situations***. New York: Perseus..

diagnoses. They occasionally carried out one treatment or study of a diagnosis, but did not work through the full diagnostic algorithm for any particular diagnosis. Lacking clinical cues that would be generated by such treatments and tests, they could not ascertain which diagnosis was most plausible, and could not resolve the problem of the blocked tube.

Finally, the *adaptive* sensemaking mode was characterized by generation of one or more plausible diagnoses of the ventilation problem and exploitation of known treatments and tests for those diagnoses. These treatments and tests, in turn, produced more clinical cues that allowed them to generate other diagnoses and rule out ones already under consideration. Unlike the fixated problem solvers who did not advance through steps of known algorithms, instead repeating the same treatment over and over, or the diagnostic vagabonds who conducted one or no treatments for a given diagnosis, the adaptive problem solvers advanced systematically through the treatment algorithm, step by step. When known approaches for a given diagnosis failed to resolve a problem, they generated other diagnoses. The combination of single-loop changes in treatments (changing and escalating treatments) and double-loop reconsideration of diagnoses based on feedback generated by the treatments allowed those in the adaptive sensemaking mode to test the accuracy of plausible diagnoses, rule some out, and resolve the clinical problem (Argyris, Putnam, and Smith, 1985).

MODEL STRUCTURE

Overview

Our representation of diagnostic sensemaking encompasses three processes that unfold and interact recursively as the doctor confronts a diagnostic challenge under time pressure. The processes are acting, interpreting, and cultivating alternative diagnoses. Our model assumes that the trigger for diagnostic sensemaking is a divergence from what people expect (Klein et al., 2005; Louis & Sutton, 1991; Mandler, 1984; Weick et al., 2005). In our source data, the doctor observes and seeks to address a serious problem with the patient. To treat the patient she needs an organizing story about what is wrong. Based on her scan of clinical signs, patient history, and timing of the problem, a plausible story develops in her mind; this takes the form of a diagnosis (Elstein, 2001; Elstein et al., 1978; Klein et al., 2006; Rudolph et al., 2004). Our model picks up the story at this point.

Acting

Catalyzed by some initial organizing story in the form of a diagnosis, the doctor launches into action. Conducting treatments and studies in diagnostic problem solving often involves following a standardized algorithm, a set of steps that can combine therapeutic treatment with diagnostic tests (Cook et al., 1994; Elstein et al., 1978). By moving through the steps of an algorithm, problem solvers generate cues that become available for them to notice, bracket, filter, and interpret. The degree to which these cues are available to the diagnostician depends directly on the progress that has been made in advancing the diagnostic algorithm: having advanced the algorithm further, the problem solver has access to a larger pool of cues for making meaning.

We model the process of advancing the algorithm and generating cues as the accumulation of progress towards an end in which the algorithm steps are complete. We represent this accumulation of progress in Figure 1 in the form of a stock and flow diagram (Sterman, 2000). A stock is a reservoir or accumulation (like water in a bathtub) and is represented by a rectangle; flows, like the spigot and drain on a bathtub, fill or drain the stock and are depicted as "pipes" with "valves." The accumulated progress is the stock labeled *Algorithm Steps Completed*. The stock is increased by *Advancing Algorithm*, a flow variable. Stocks have a key role in creating dynamics: they create delays, give systems inertia, and provide systems with memory (Repenning & Sterman, 2002). For example, accomplishing steps in the diagnostic algorithm takes time (delays), sets the problem solver on a course of action (inertia), and yields results that remain available for interpretation (memory).

Insert Figure 1 about here.

To define the pace at which the doctor advances the algorithm, we assume a limit or end that would define a fully complete algorithm according to accepted medical practice. This creates an index ranging from 0 to 1, where 1 signals a fully completed algorithm. Our source data show that treatment algorithms for the four most commonly considered diagnoses averaged about four steps. We further assume that the doctor moves the algorithm towards completion at a pace that accomplishes a constant fraction of the remaining algorithm, where that fraction is defined by the *Time Needed to Advance Algorithm*. This time constant captures the time delays associated with mental organizing to do the test, physical rearranging to prepare for the test, conducting the test, awaiting a physiological response from the patient, and noticing the results as cues in the stream of ongoing experience. The time constant of 8 minutes to complete the algorithm used in baseline simulations produces a good match with the number of algorithm steps completed and diagnoses doctors considered during the approximately 25 minute scenarios in the source data. (Later, we change *Time to Advance the Algorithm* in sensitivity analyses to examine how a different pace of acting influences sensemaking.)

Advancing the diagnostic algorithm makes *Cues Available*. As the doctor accomplishes the algorithm, she generates new diagnostic information that she uses in the sensemaking process to update how plausible she considers her leading diagnosis (which we label *Plausibility of Leading Diagnosis* and will define more fully in the next section). When working on the correct diagnosis, the cues are more likely to confirm or favor the leading diagnosis; when working on an incorrect one, they are more likely to be disconfirming. We distinguish a correct from an incorrect diagnosis with the binary variable *Accuracy of Leading Diagnosis,* where a value of 0 means the current or leading diagnosis is incorrect and a value of 1 means it is correct. (The diagnostician does not know the accuracy of the diagnosis, but this variable has utility as a modeling construct to control the stream of cues.) When the algorithm is complete, *Cues Available* will equal the *Accuracy of Leading Diagnosis*. When the algorithm begins, *Cues Available* will equal *Starting Plausibility of Leading Diagnosis,* a model variable (not shown in the figure) that is reset each time a new diagnosis takes over as the leading diagnosis.[3] The stock of *Algorithm Steps Completed* is the fraction of the algorithm completed, so it indicates the fraction of the difference that has been revealed at any given time between the *Starting Plausibility of Leading Diagnosis* (not depicted) and the *Accuracy of Leading Diagnosis*. Formally, the equations for Figure 1 are:

$$\text{Algorithm Steps Completed } (t) = \int_t(\text{Advancing the Algorithm } (s)\ ds)$$

[3] The *Plausibility of New Diagnosis* takes the value of *Plausibility of Leading Diagnosis, at which time* the new algorithm begins and then stays constant until the next algorithm starts.

Advancing the Algorithm *(t)* = (1 - Algorithm Steps Completed *(t)*) / Time Needed to Advance Algorithm

Time Needed to Advance Algorithm = 8 minutes

Cues Available (t) = Starting Plausibility of Leading Diagnosis *(t)* + Algorithm Steps Completed (*t*)* (Accuracy of Leading Diagnosis *(t)* – Starting Plausibility of Leading Diagnosis (t))

Starting Plausibility of Leading Diagnosis (t_0) = 0.5

Accuracy of Leading Diagnosis *(t)* = (0 if incorrect, 1 if correct).

Updating

Considerable prior research suggests that plausibility is the engine of sensemaking; a plausible diagnosis is what allows people to move forward with problem solving (De Keyser et al., 1990; Weick, 1988; Weick et al., 2005). Studies of medical decision making (Elstein, 2001; Elstein et al., 1978; Johnson et al., 1982), tactical decision-making under stress (Cannon-Bowers et al., 1998), problem detection (Klein et al., 2005; Mandler, 1982), and naturalistic decision-making (Klein et al., 1993; Snook, 2000; Zsambok & Klein, 1997) indicate that the perceived plausibility of the leading diagnosis waxes and wanes, that changes in this level are not instantaneous, and that delays in updating directly influence problem solving. To capture these attributes, we model *Plausibility of the Leading Diagnosis* as a stock that can increase or decrease (see Fig. 2). A crucial feature of our model is the fact that people's sense of how plausible the leading diagnosis is at any time does not change instantaneously but, instead, happens with a delay.

Insert Figure 2 about here.

In our model, the doctor uses the *Cues Available* to update beliefs about the *Plausibility of Leading Diagnosis*. We define *Plausibility of Leading Diagnosis* as a measure ranging from 0 to 1 that captures the diagnostician's belief that the leading diagnosis will solve the problem; 1 indicates the highest possible perceived plausibility. We define a construct that represents the aggregation of the most recently available information about the leading diagnosis, which we show in Figure 2 as the *Plausibility from New Cues.* For now, let us say this is equal to the *Cues Available*, as defined previously. We will introduce a difference in these two concepts in the next section when we incorporate self-fulfilling interpretations. *Updating* (the flow) is the process by which the current view of the *Plausibility of Leading Diagnosis* (the stock) is adjusted to equal the *Plausibility from New Cues*. The stock represents the net accumulation of whatever updating has occurred; it "remembers" the cumulative results of the updating process. Updating is not instantaneous; it requires time for people to contemplate new information, match it with previous experience, and assess how plausible the current diagnostic story is (Berner & Graber, 2006; Elstein et al., 1978; Gaba, Maxwell, & DeAnda, 1987; Klein et al., 1993; Raufaste, Eyrolle, & Marine, 1998). The time constant for this process is the *Time Needed to Update*. Because updating should be relatively fast compared to acting, which was given an 8 minute time constant, we chose a value of 2 minutes for this parameter. Formally,

Plausibility of Leading Diagnosis (t) = $\int_t$ Updating(s) ds + Starting Plausibility of Leading Diagnosis (t_0)

Updating (t) = (Plausibility from New Cues (t) - Plausibility of Leading Diagnosis (t)) / Time to Needed Update.)

Time to Needed Update = 2 minutes

Interpreting

How plausible people consider a particular diagnosis or situation assessment influences whether they stick with the current assessment and exploit standard operating procedures and treatment algorithms for that diagnosis or step back to think about and generate new possibilities. Research suggests that when people are skeptical of a diagnosis, i.e., when perceived plausibility of the leading diagnosis is low, they pay careful attention to external cues as a way to gain more information and revise the diagnosis (Cohen, Freeman, & Thompson, 1998; Cohen et al., 1996; De Keyser et al., 1990; Klein et al., 2005). As *Plausibility of Leading Diagnosis* rises, the weight they place on external cues declines. New external cues are ignored, discounted, or interpreted in favor of the current leading diagnosis (Johnson et al., 1982; Johnson et al., 1988; Klein et al., 2006; Luchins & Luchins, 1950; Reason, 1990).

To incorporate the influence of current beliefs on interpretation, we introduce two new variables in Figure 3. The *Weight on Cues* depends on the *Plausibility of the Leading Diagnosis*, and the *Effect of Plausibility on Weights* defines this dependency relationship. We model *Plausibility from New Cues* as the weighted average of the objectively correct information available (*Cues Available*) and an anchor (taking the value 1) representing the belief that the current hypothesis is correct. Formally,

Plausibility from New Cues (t) = Cues Available from Algorithm (t) *Weight on Cues (t)
+ (1 - Weight on Cues (t))

With this weighted average, when the *Weight on Cues* is 1 (at its maximum), the *Plausibility from New Cues* equals the *Cues Available*, indicating the doctor is attending fully to all available cues. When the *Weight on Cues* is 0 (at its minimum), the *Plausibility from New Cues* will be 1, indicating the doctor is so committed to or confident in her current diagnosis that she does not attend to any cues.

Insert Figure 3 about here.

To specify the *Weight on Cues*, we must formalize the linkage between how plausible the problem solver considers the current diagnosis (*Plausibility of the Leading Diagnosis)* and the interpretation of cues. Research on diagnostic error, fixation errors, garden path errors, and tunnel vision supports the notion that as the plausibility of the current diagnosis rises, openness to external cues, represented by the weight they place on external cues, especially ones that defy the current view, decreases (Cook et al., 1988; Cook et al., 1994; De Keyser et al., 1990; Johnson et al., 1988; Luchins et al., 1950; Staw, 1976; Staw, Sandelands, & Dutton, 1981; Xiao et al., 1995). In other words, *Weight on Cues* is a downward-sloping function of *Plausibility of Leading Diagnosis*.

However, prior research is surprisingly silent regarding the exact form of this relationship between weight given to external cues and plausibility. Drawing on the behavior of diagnosticians in our source data, we induced a representation of the relationship between *Plausibility of the Leading Diagnosis* and *Weight on Cues*. First, we say that when *Plausibility of Leading Diagnosis* is at its extreme value of 0 (the problem solver has no confidence in their diagnosis), the *Weight on Cues* should be at its extreme value of 1 (the problem solver pays full attention to cues). Conversely, when *Plausibility* equals 1, the *Weight on Cues* should equal zero. Second, we note that the effect of changes in plausibility on cue weight may vary across individuals (Klein et al., 2006; Klein et al., 2005; Lesgold et al., 1988; Raufaste et al., 1998). We chose a functional relationship that allows us to capture such differences. Thus,

Weight on Cues (*t*) = (1 - Plausibility of Leading Diagnosis (*t*)) ^ Effect of Plausibility on Weights where the exponent *Effect of Plausibility on Weights* is a parameter chosen to represent possible individual and/or situational differences. Appendix 1 shows the shape of this function for several values of the parameter, and in the next section we explore how changes in this parameter affect model behavior.

The new links in Figure 3 close a feedback loop that has an important effect on the dynamics of the system. Consider the response when there is a small increase in the *Plausibility of Leading Diagnosis*. The *Weight on Cues* decreases slightly, leading to a small increase in the *Plausibility from New Cues* (because with less weight on cues, the anchor – which is the maximum value for plausibility – is weighted more heavily), which in turn causes *Updating* to rise, further increasing the stock *Plausibility of Leading Diagnosis*, and the process continues. The interpretation process amplifies a change in a reinforcing feedback process (labeled with the loop identifier "R" for Reinforcing). We name this feedback loop the "Self-Fulfilling Interpretation loop." In the absence of any offsetting influences, this loop pushes the plausibility of an early-generated diagnosis toward ever great plausibility. If the loop is driving toward ever-greater plausibility of an erroneous diagnosis, it will generate the well-known self-confirming pattern of fixation, in which an initially plausible diagnosis and the filtering of external cues recursively influence each other so that the problem solver sticks to the diagnosis despite cues he is on the wrong track. If the loop is driving toward ever-greater plausibility of a correct diagnosis, this is salutary. As we demonstrate later, the interplay between this interpretation process and the processes of acting, gathering cues, and cultivating alternative diagnoses gives rise to the distinctive patterns of sensemaking in Rudolph's study.

Cultivating Alternatives

Changes in *Plausibility of Leading Diagnosis* are accompanied not only by changes in attending to external cues, but also changes in internal sensemaking processes. Our source data as well as in-depth case studies of diagnostic sensemaking indicate that problem solvers extract cues to support a leading diagnosis while at the same time elaborating a second, alternative diagnosis (Rudolph, 2003; Klein et al., 2006; Weick et al., 2005). Several processes are at play. First, when perceived plausibility of the leading diagnosis or schema is low, people tend to generate and consider other ways of looking at the situation (Bartunek, 1984; Dörner, 1997; Klein, 1998; Klein et al., 2006). Second, people conduct "mental simulations" to explore the likely impact of new diagnoses or courses of action (Klein, 1998). Third, this process of elaborating alternative diagnoses is likely to be non-linear. Based on an accumulation of cues discrepant with the leading diagnosis, the problem solver suddenly (not gradually) abandons this diagnosis and it is replaced by an alternative (Klein et al., 2005). Each of these processes takes effort, thought, and time. To evoke the time and effort involved, we combine them under the label *Cultivating* alternative diagnoses. Figure 4 depicts our representation of this process.

Insert Figure 4 about here.

Our formulation for cultivating an alternative diagnosis is directly analogous to the formulation for advancing the algorithm. Here, the stock is the *Plausibility of Alternative Diagnosis*. The inflow, named *Cultivating,* increases the stock towards its maximum value of 1 at a pace governed by a time constant, the *Time Needed to Cultivate*. For our baseline simulations, we chose a value of 4 minutes for this time constant, between the time for advancing the algorithm and the time for updating. As shown in Figure 4, there is also an *Effect of Current Plausibility on Alternative* that slows down the pace of cultivating when the *Plausibility of the Leading Diagnosis* is high. We model this effect so that below a threshold value (*Plausibility of Leading Diagnosis* = 0.5), *Cultivating* continues at the normal pace, and above the threshold the pace declines linearly to equal zero when *Plausibility* reaches its maximum of 1. Formally,

Plausibility of Alternative Diagnosis (t) = $\int_t$(Cultivating $(s)\, ds$)

Cultivating (t) = Effect of Current Plausibility on Alternative (t) *(1 - Plausibility of Alternative Diagnosis (t)) / Time Needed to Cultivate;

Effect of Current Plausibility on Alternative (t) = Min (1, 2-2*Plausibility of leading diagnosis (t));

Time Needed to Cultivate = 4 minutes;

To describe how the diagnostician switches from one leading diagnosis to another, we assume the she holds a leading diagnosis until an emerging alternative becomes more plausible in her view, at which time the alternative takes over the role of leading diagnosis. To implement this logic in our model, we define a *Change Trigger* as the condition that the *Plausibility of Alternative Diagnosis* is greater than the *Plausibility of Leading Diagnosis*. When this trigger occurs, the model tracks the change by resetting the three stocks. *Plausibility of Leading Diagnosis* takes the value at that time for the *Plausibility of Alternative Diagnosis*, and the stock for *Plausibility of Alternative Diagnosis* is set to zero ready to be filled by cultivating yet another alternative. The stock of *Algorithm Steps Completed* is also set to zero, ready to be filled by steps in the new algorithm. The dotted lines in Figure 5 are a summary notation to signal these changes when the leading diagnosis is switched. Details of how the switching process is implemented in the model are in the Appendix.

Insert Figure 5 about here.

RESULTS: THE DYNAMICS OF ACTION-ORIENTED SENSEMAKING

We now use simulation analysis of our model to show how different patterns of diagnostic sensemaking arise from the interplay of acting to advance the algorithm, interpreting cues to update plausibility of the leading diagnosis, and cultivating new diagnoses. To develop the main insights, we begin with a set of experiments that show how the simple underlying structures of our model produce the behavior visible in the four modes of diagnostic sensemaking observed in our source data. In the experiments that follow, we control for the effects of random search by assuming that all diagnosticians generate alternative diagnoses in the same sequence. Specifically and consistent with the modal sequence in the field data, we say that the first, second, and third diagnoses considered are incorrect, the fourth is correct, and the fifth and all others after that are incorrect. (More extensive simulation analysis not presented here confirms that results highlighted here are replicated under various other search assumptions.)

Four modes of diagnostic sensemaking

As our simulations begin, the doctor is considering the first (incorrect) leading diagnosis with a moderate level of plausibility (set to 0.5 (out of 1.0) in the initial conditions). To highlight differences among the four sensemaking modes we display in Fig. 6 the behavior of the *Plausibility of the Leading Diagnosis* over time.

Adaptive Sensemaking

To clarify the impact of differences in the interplay among acting, interpreting cues, and cultivating diagnoses, we begin with an illustration of the adaptive mode of diagnostic sensemaking (See Figure 6). The problem solver's sense of the plausibility of the first diagnosis begins at its initial value of 0.5 and three things begin to occur simultaneously. First, the doctor begins acting - advancing the algorithm associated with the first diagnosis. The stock of *Algorithm Steps Completed* increases, and the *Cues Available* increase as well. Second, in the interpretation process, the *Weight on Cues,* capturing how open the problem solver is to external cues, starts to decline slowly as the Self-Fulfilling Interpretation Loop drives an increase in plausibility. In the first few moments, the doctor has done little to advance the diagnostic algorithm, so the limited cues have little effect on plausibility. After a short time, the accumulated cues (which are "objectively" disconfirming information because the first diagnosis is incorrect) begin to show their effect on plausibility, and we see a slow decline in the *Plausibility of the Leading Diagnosis*. Meanwhile, the third process unfolding is the cultivation of an alternative diagnosis. The plausibility of this alternative diagnosis builds as the doctor considers it in the face of cues unfavorable to the leading diagnosis. Eventually, the declining plausibility of the first diagnosis coupled with increasing plausibility of the alternative reaches a point where the alternative has a higher plausibility than the leading diagnosis. At this moment, the first diagnosis is rejected, and the second diagnosis becomes the leading diagnosis. The doctor begins pursuing the algorithm associated with the second diagnosis, the new leading diagnosis. As before, plausibility increases for a short while, disconfirming cues accumulate and begin to cause a reduction in plausibility, and an alternative diagnosis gains favor and eventually overtakes the leading diagnosis.

As Figure 6 shows, the pattern continues with sensemaking processes regarding diagnoses two and three. When the doctor begins to consider diagnosis number four, the correct one, plausibility initially begins to grow as before. However, the new cues available as algorithm steps are completed offer confirmation of this diagnosis and are interpreted to build even more plausibility in the leading diagnosis. Moreover, the Self-Fulfilling Interpretation loops reinforces the increases in plausibility, reducing the Weight on Cues thus boosting plausibility still further. The diagnostician pursues the treatment and study algorithm to completion and converges on a steady state choice of the correct diagnosis.

Insert Figure 6 about here.

The simulation in Figure 6 shows two important features of the dynamics that arise from the interplay among acting, interpreting, and cultivating alternatives. First, the consideration of each diagnosis in a sense enjoys a honeymoon period during the time it takes for an alternative diagnosis to emerge as a viable contender as the basis for action – a temporal interplay between a leading and an alternative diagnosis. In the adaptive sensemaking mode of Figure 6, this temporal interplay is “well-balanced” in that the honeymoon period is long enough for the doctor both to take action and to interpret the results stirred up by that action for both the incorrect and correct diagnoses she considers. Second, there is a dynamic interchange in the roles of acting and interpreting because the cues available accumulate slowly relative to the ongoing process of interpreting experience. The result we see in Figure 6 is that for each new diagnosis the first thing that happens is that plausibility increases but then later (for each incorrect diagnosis) decreases. Plausibility increases at first because few cues are available and updating driven by the cognitive interpretation process occurs relatively quickly. But meanwhile, the doctor continues to interact with the physical world by advancing the algorithm and generating more cues. As the disconfirming evidence mounts, it eventually overcomes the effects of the self-fulfilling interpretation. Plausibility reaches a peak and then begins to decline as disconfirming evidence continues to mount.

Fixating

Figure 7 shows simulation results that replicate the fixating mode of diagnostic sensemaking. The only difference between this experiment and the one in Figure 6 is a change in the interpretation process: the *Effect of Plausibility on Weights* is stronger in Figure 7 (specifically, *Effect of Plausiblity on Weights* = 1). Again, the first diagnosis the doctor generates is incorrect (by assumption and consistent with the field study data). The simulation begins as before with an initial plausibility of 0.5 that starts to rise at first due to self-fulfilling interpretations. However, in contrast to the adaptive mode, the lower *Weight on Cues* in this scenario allows the self-fulfilling process to gain momentum. As the diagnostician acts, she interprets cues and creates meaning that supports the current diagnosis, and the *Weight on Cues* falls even more. The process of constructing meaning to support the current diagnosis gains strength. The Self-Fulfilling Interpretation loop reinforces the current diagnosis, and because the loop is so strong, the first diagnosis is always preferred to an alternative that might be considered. The diagnostician does not move on to any other diagnosis. The strong reinforcing effects of the Self-Fulfilling Interpretation loop result in fixating, a pattern of diagnostic problem solving in which the doctor is completely confident in the incorrect diagnosis. Self-fulfilling interpretations filter out some of the available disconfirming evidence, so the current diagnosis locks in prematurely, squeezing out the cultivating of alternative diagnoses, and the doctor never has a chance to find the correct diagnosis. The outcome is a false positive convergence on the incorrect diagnosis, a Type I error in diagnostic sensemaking.

Insert Figure 7 about here.

Diagnostic Vagabonding

Figure 8 shows simulation results that replicate the vagabonding mode of diagnostic sensemaking. The difference between this experiment and the one in Figure 6 is in the interpretation process: the *Effect of Plausibility on Weights* is weaker in Figure 8 (specifically, *Effect of Plausibility on Weights* = 0.15). In this simulation, the first three diagnoses are rejected as before because a better alternative had emerged, but compared to the adaptive case in Figure 6, these diagnoses are rejected more quickly. This implies that the doctor in this scenario does not advance the algorithm as much, consistent with the field data which showed that diagnostic vagabonds generated diagnoses but performed few or no steps of the treatment/test algorithm. When the third diagnosis is rejected, the fourth becomes the leading diagnosis, and we begin to see important differences compared to the adaptive case. The plausibility of the leading diagnosis, now a correct one, increases, but not as rapidly as in the adaptive case. Here our stylized doctor places a higher weight on cues (due to a weaker effect of plausibility on weights), but the cues to confirm the diagnosis accumulate somewhat slowly because they must be made available by acting to advance the algorithm. Meanwhile, an alternative diagnosis gains favor and eventually overtakes the correct diagnosis to become the preferred one. In contrast to the adaptive mode, the doctor in this scenario also rejects the correct diagnosis number four. Once this diagnosis is rejected, the doctor continues identifying alternatives, choosing them as the leading diagnosis, and rejecting them in favor of the next emerging alternative.

The error in this mode is the premature rejection of the correct diagnosis number four, a false negative or Type II error in diagnostic sensemaking. The stylized doctor in this simulation is quite capable of cultivating new diagnoses and of attending carefully to cues, but lacking more confident beliefs about the plausibility of a diagnosis she does not hold onto it long enough to adequately advance the algorithm for any one diagnosis. The result is vagabonding, a pattern of diagnostic problem solving in which the doctor jumps from one plausible diagnosis to the next without treating the patient. The dynamic interplay among acting, interpreting, and cultivating alternatives is out of balance: the doctor yearns for clarifying information (interpreting) but the pace of generating and new cues associated with the leading diagnosis (acting) is too slow relative to the pace of cultivating alternatives. The doctor gets stuck in a steady state of generating new alternative diagnoses but not discovering enough about these diagnoses to reach an effective conclusion. This mode of diagnostic problem solving fails because the effect of plausibility on interpretation is so weak that even the correct diagnosis is rejected.

Insert Figure 8 about here.

Stalling

The model can also generate a mode of sensemaking in which the doctor is stalled, unable to move forward to advance any algorithm. One such scenario is a stylized doctor with an *Effect of Plausibility on Weights* like the vagabond and for whom both advancing the algorithm and gaining plausibility of a new diagnosis are extremely slow processes (represented in the model with high values for the *Time Needed to Advance Algorithm* and *Time Needed to Gain Plausibility*). A simulation with these settings, not shown here, yields a flat line for plausibility, stuck at its initial value. Rudolph's analysis classified only 2 out of 39 doctors as stalled, and both exhibited behaviors of advancing the algorithm little or not at all and establishing working diagnoses very slowly, consistent with this story. However, with so few examples and so little action to learn from, we omit this mode from subsequent analysis.

The experiments so far show how the feedback structure in our model of diagnostic decision making (Figure 5) generates the modes of diagnostic problem solving observed in the field study. Stalling occurs when the diagnosticians do not generate proposed diagnoses. Fixating occurs when they do not discard an incorrect diagnosis, never discovering the correct hypothesis. Vagabonding occurs when they do not determine a correct diagnosis to be so and thus prematurely discard it. Adaptive problem solving occurs only when they both discover the correct diagnosis and determine that it is the correct one.

Sensitivity analysis: The interplay of acting, interpreting, and cultivating diagnosis

To highlight the critical dynamic interactions among interpreting cues, advancing the algorithm, and cultivating alternative diagnoses, we present a set of experiments in which we vary the pace of these processes. Although fixation, adaptive sensemaking, and vagabonding could be generated by varying only the *Effect of Plausibility on Weights,* we gain further insight about the combinations of processes and limiting conditions for such behaviors.

We begin with a set of simulations in which all parameters are identical to the ones used for the scenario that results in vagabonding (Figure 8) except that we vary the pace at which the doctor advances the algorithm by setting the *Time Needed to Advance Algorithm* to values ranging from very fast (1 minute) to very slow (16 minutes). Figure 9 shows the first experiment comprising eleven simulation runs that separate into two distinctly different patterns. One set, corresponding to the faster advancing of algorithm steps, displays adaptive sensemaking in which the plausibility of diagnosis number four climbs smoothly toward one. The other set, corresponding to the slower advancing of algorithm steps, displays vagabonding in which diagnosis number four is rejected and new alternative diagnoses continue to move into position as leading diagnoses. Different rates of advancing the algorithm generate qualitatively different dynamics: the doctor converges on the correct diagnosis for fast rates of advancing, but rejects it when the rate of advancing is too slow. The results highlight an important feature of the systems' dynamics: more action (advancing the algorithm faster) offsets the effects of less self-fulfilling interpretation, and protects the problem solver from being swept into vagabonding mode. Small differences in the rate of advancing can mean the difference between adaptive sensemaking and vagabonding. This result raises the question as to just what pace of advancing is needed to escape from the perils of vagabonding.

Insert Figure 9 about here.

To shed light on this question, we conducted an extensive set of experiments to test the relationship among the pace of advancing the algorithm, the pace with which an alternative gains plausibility, and the strength of the effect of plausibility on interpretation. We performed sets of simulations similar to those in Figure 9 for various values of the *Effect of Plausibility on Weights.* In each set of simulations, we identified the threshold *Time Needed to Advance Algorithm* that distinguished adaptive sensemaking from vagabonding. In other words, we found the pace of advancing needed to achieve adaptive sensemaking for the given combination of the other two parameters. For example, from the set of simulations shown in Figure 9, we can determine that a pace of advancing faster than 7 minutes for the *Time Needed to Advance Algorithm* will yield adaptive sensemaking, and a slower pace will yield vagabonding. Indeed, diagnostic vagabonds rarely advanced the algorithm beyond the first step or did so up to 15 minutes into the scenario. The results, displayed in Figure 10, show that for weaker *Effects of Plausibility on Weights*, faster advancing of the algorithm is needed for adaptive sensemaking. A weak interpretation effect describes a doctor who wants more cues, so the pace of acting must be faster in order to lead to adaptive sensemaking. When the appetite for cues is high (weak effect), slow action induces vagabonding. Conversely, a modest degree of confidence in the leading diagnosis contributes to the robustness of the sensemaking process by thwarting the lurking threat of vagabonding.

Insert Figure 10 about here.

To fully characterize the dynamic interplay among the processes of acting, interpreting, and cultivating alternatives, we repeated the analysis for several values of the *Time Needed to Gain Plausibility*. The resulting family of curves (Figure 11) shows how the threshold pace of advancing the algorithm depends on both the *Effect of Plausibility on Weights* and the *Time Needed to Gain Plausibility*. As the strength of the interpretation effect increases, the threshold pace of advancing needed for adaptive sensemaking gets slower. When the pace of cultivating alternatives is very fast, the risk of vagabonding is quite high and not mitigated much by stronger interpretation effects; very rapid action is still needed. For a slower pace of cultivating alternatives, small increases in the strength of the interpretation effect yield larger improvements in the robustness of the sensemaking process: slower paces of action are still adequate to achieve adaptive sensemaking.

Insert Figure 11 about here.

DISCUSSION

Our simulation model is able to generate the four modes of diagnostic sensemaking identified in Rudolph's study. Stalling occurs when the diagnosticians are unable to generate a diagnosis they consider plausible enough to launch action. Fixating occurs when the leading diagnosis quickly, but erroneously, gains plausibility; problem solvers do not discard their leading diagnosis and never discover one that solves the problem. Vagabonding occurs when the leading diagnosis does not gain enough plausibility to sustain concerted action; even if people hit upon a diagnosis that solves the problem, they do not recognize it. Adaptive diagnostic sensemaking occurs when the leading diagnosis gains enough plausibility to sustain concerted action, but not too much to prevent alternatives from emerging.

Our modeling and analysis contribute three new insights to understanding sensemaking in high-stakes, time-pressured settings. First, we highlight self-fulfilling interpretation as beneficial for adaptive sensemaking. While much research has documented the liabilities of self-fulfilling cognitive processes such as confirmation bias and fixation, we show that such processes have benefits in staving off diagnostic vagabonding, preventing stall-outs in sensemaking, and steadying sensemaking processes so that diagnoses can be redrafted with the benefit of new cues. Second, understanding the challenges of sensemaking under time pressure requires a more finely differentiated conceptualization of processes that contribute to fixation. Third, we show that the dynamic interplay of acting, interpreting cues, and cultivating new diagnoses opens and closes windows of opportunity for adaptive sensemaking. There are critical moments when each of these sub-processes can remediate weaknesses in the others, after which the missteps of dysfunctional sensemaking can no longer be remedied. These insights have important implications for both scholarly research on and practical approaches to improving time-pressured sensemaking.

The benefits of self-fulfilling interpretation in sensemaking. Earlier work on sensemaking has argued persuasively that a plausible diagnosis or story (rather than a perfectly accurate one) is not only adequate, but often optimal to launch effective action (Sutcliffe & Weber, 2003; Weick et al., 2005). Our analysis indicates that beyond its crucial role in *launching* action, plausibility also plays a critical role in *sustaining* action. The problem solver's sense of the plausibility of a diagnosis provides useful momentum to keep moving on a current course of action (i.e., the current algorithm). The counter example of the diagnostic vagabonds highlights the importance of this inertia. When the diagnostic vagabonds considered the correct diagnosis, they discarded it because feedback processes undermined rather than intensified the plausibility of their leading diagnosis. Without an increasing sense of plausibility, they were unable to hold the leading diagnosis firmly enough to sustain therapeutic and diagnostic action.

One of the challenges of time-pressured sensemaking is the ongoing competition between the plausibility of the leading and the alternative diagnoses. Following an algorithm or standard operating procedure sustains the current story; it enacts the current story. Without this sustained action, cues needed to build a sense of plausibility do not surface. Especially when the cues that become available early are ambiguous, a little bit of fixation is essential to keep the problem solver on track long enough for a critical mass of cues to accumulate. Self-fulfilling interpretation allows problem solvers to do what Klein and colleagues call "preserving the frame" (Klein et al., 2006) long enough to sustain needed action and allow the leading diagnosis to win the competition with alternative diagnoses.

A nuanced continuum of self-fulfilling interpretation and fixation. We have argued that some self-fulfilling interpretation is needed to build a person's sense that their point of view is plausible and thereby promote adaptive sensemaking. Previous discussions of fixation error have noted that a distinctive presentation or unfolding of the problem locks people into a sense that their (erroneous) diagnosis is highly plausible or correct (cf Johnson et al., 1988; De Keyser and Woods, 1990). Our model captures this idea that as one's perceived sense of plausibility increases, openness, especially to disconfirming cues, decreases. Paradoxically, some self-fulfilling interpretation, or holding to a diagnosis despite some countervailing cues, allows a richer range of cues and alternative diagnoses to emerge.

Further, our model elaborates a detailed representation of the relationship between the increasing sense of plausibility and openness to external cues. Appendix 1 provides four hypothetical examples that illustrate different degrees of impact of plausibility on openness, ranging from when the problem solver is always completely open to cues (no impact of plausibility) to when openness is directly and inversely proportional to plausibility. Our simulations showed the importance of this relationship: changes in the shape of the relationship between different levels of plausibility on openness to cues alone can produce sensemaking modes ranging from vagabonding through adaptive to fixation. This captures the ideas of March and Sastry also based on computer simulations, that learning from experience can suffer from being either too slow or too fast (March, 1991; Sastry, 1997).

Balancing and reinforcing feedback as building blocks of sensemaking. Our analysis highlights dualities in the three processes of sensemaking we mapped. Although deliberation is often crucial to effective action, in diagnostic sensemaking under-time pressure, acting quickly, even on an uncertain diagnosis, can mitigate the effects of slow interpretation. Although self-fulfilling interpretation can lead to fixation, it is crucial to adaptive sensemaking. Although generating new diagnoses is crucial to adaptive sensemaking, when it happens too fast, it can be a liability. These dualities express the dynamics of underlying balancing and reinforcing feedback processes.

Sensemaking theorists and some decision theorists have argued that feedback provides balancing loops that improve problem solving. Sensemaking theory argues that if people generate plausible diagnoses (or stories) and begin to act on them, this action will stir up corrective feedback, through balancing loops, that will allow people to "[redraft] an emerging story so that it becomes more comprehensive, incorporates more of the observed data, and is more resilient in the face of criticism" (Weick et al. 2005: 412). Similarly, the on-going processes in dynamic problem solving environments provide frequent corrective feedback from new cues generated by action, making such environments more forgiving than simple static judgment tasks (Kleinmuntz, 1985; Hogarth, 1981). However, in contrast to the presumed balancing feedback processes that improve the fit between the current diagnosis and the correct one, the self-fulfilling interpretation loop in our model is a reinforcing or positive feedback loop that acts to amplify small changes and create both virtuous and vicious cycles that can be destabilizing.

Thus, the self-reinforcing interpretation process interacts with the therapeutic and diagnostic actions and generating of new diagnoses to open and close windows of opportunity for adaptive sensemaking. These critical moments occur when there is a close competition between the leading and the alternative diagnosis. Under the time pressure assumed in our model, there are two generic failure modes from which problem-solvers cannot recover: Just at the moment when the problem solver could disconfirm the leading diagnosis and switch to another, the momentum of the self-fulfilling feedback loop sweeps her into fixation. Or, just at the moment when sticking with the leading diagnosis would help advance the appropriate treatment algorithm, the combination of rapid generation of alternative diagnoses and slow accumulation of cues sweeps her into vagabonding.

The self-fulfilling interpretation loop presented here can act benignly to strengthen a nascent diagnosis so that it is more resilient in the face of disconfirming evidence, but can also act malignly to weaken faith in a plausible diagnosis so that it loses out to a less good one, or to strengthen faith in a poor diagnosis that should be discarded. Fixation can arise if the effect of plausibility on cue interpretation is very strong; neither acting swiftly to generate cues, nor deftly cultivating alternative diagnoses will make a difference. When the effect of plausibility is moderate, small changes in acting to advance the algorithm can open or close the window on adaptive sensemaking. When the leading diagnosis is incorrect, a slower pace generates fewer disconfirming cues, allowing plausibility of the leading diagnosis to gain crucial early ground that quickly squeezes out gains for the alternative. A faster pace of acting allows the alternative diagnosis to gain ground and eventually overtake the leading one.

Improving sensemaking in practice. Our analysis points to several promising avenues for improving time-pressured sensemaking. First, whereas scholars have previously identified a range of strategies to mitigate the risks of falling prey to fixation, our work suggests the need to also develop ways to overcome the risks of diagnostic vagabonding. Ironically, too much success in training diagnosticians to avoid fixation may increase the tendency to move quickly from diagnosis to diagnosis and lock in to a mode of vagabonding. We offer some propositions about situations that pose a high risk of vagabonding: 1) When urgency is high, when more is at stake, when situational factors constrain or slow down the ability to take action and gather information, and when there are many plausible alternatives, vagabonding will be more likely; 2) When these factors are coupled with slower or less confident interpretation processes, as might be expected with novel problems or relatively inexperienced problem solvers, the risk of vagabonding will be greater; and 3) These results imply that potential strategies to avoid vagabonding are to slow down the pace of cultivating alternatives, take action more confidently, and hold leading diagnoses more confidently to allow more cues to surface. These three strategies interact and support each other, so improvement in one dimension can compensate for a shortfall along another.

The second set of strategies to improve sensemaking addresses constraints on the processes of acting, interpreting, and cultivating alternatives. Some sensemaking settings present only minor constraints, yet other settings may impose significant limits on one or more of these processes. The pace of action might be limited by resource constraints, technological factors, or physical factors such as the time needed to conduct certain activities and for a physiological response from the patient to develop. The set of possible actions may be limited when urgency rules out actions that simply take too long. The ability to adjust self-fulfilling interpretation effects might be limited by people's ability to be mindful of or "bystand" their own diagnostic frames rather than mistaking them for reality (Kegan, 1994; Langer, 1989; Torbert, 1991). The pace of generating alternatives might be limited by cognitive capacity in light of other demands for attention and by knowledge and experience relevant to the problem at hand. Constraints such as these mean that the recipe for combining acting, interpreting, and cultivating alternatives that fits one situation may not be feasible in others. Just as a virtuoso musician will learn to play over a range of loudness, the versatile problem solver will develop the ability to adjust the pace of acting, interpreting, and cultivating alternatives to match the needs of the situation. However, this is a difficult challenge when the environment is novel or complex, time is short, and stakes are high. Such expertise develops over considerable time and exposure to a variety of situations; experience in problem solving under routine circumstances is not sufficient to foster development of this meta-skill.

Limitations and future research. Our theory development approach based on computer simulation offers a relatively new way to hold a conversation between theory and data. We recognize that our source data is a single study of medical residents in only one scenario, itself a high-fidelity simulated training experience. Both the restricted context of the source data and the nature of simulation mean that our model of diagnostic sensemaking excludes many features of real-world problem solving. We have not explicitly modeled the status of the patient, nor have we included group-level aspects of sensemaking. Moreover, we have not captured the range of the doctor's actions that do not directly advance the algorithm or the effects of emotion. There is much room for future research to continue the theory development process in diagnostic decision making and other theory contexts. Field research or future modeling efforts could test or explore the theoretical and practical implications of stronger and weaker effects of perceived plausibility on openness to external cues. More empirical and computational studies are needed of the relationships between balancing and reinforcing loops in complex problem-solving situations.

CONCLUSION

This paper developed a grounded theory about the role of plausibility in action-oriented sensemaking by drawing on existing theory and empirical data. The theory we developed is represented by a mathematical model portrayed in causal loop diagrams and simulated by computer. The mathematical model rigorously articulates, through the constraints of linked, internally consistent equations, underlying structures and relationships that produce various sensemaking modes: stalling, fixating, vagabonding and adapting. The formal modeling process helped extend existing sensemaking theory in three ways: 1) it has clarified core dynamic elements of inertia and change in acting, interpreting, and generating new diagnoses (i.e. the stocks and the flow equations that represent each process). 2) It has taken narrative theories of sensemaking that assert interactions among acting, interpreting, and revising diagnoses and represented the interactions explicitly (e.g., how the pace of generating new cues influences assessments of plausibility and the need for cultivating alternate diagnoses). 3) Most importantly, it has generated new insights suggesting that sensemaking theory must include both balancing and reinforcing processes. Specifically, the formal modeling process has allowed us to demonstrate the benefits and nuances of self-fulfilling interpretation; some fixation-like activity is needed for adaptive diagnostic sensemaking (but too much can cause problems). Through modeling we have also demonstrated that the specific form of the relationship between faith in the plausibility of the current diagnosis and openness to new cues is more complex than previous theories of sensemaking and fixation have appreciated; this is a fertile ground for future research.

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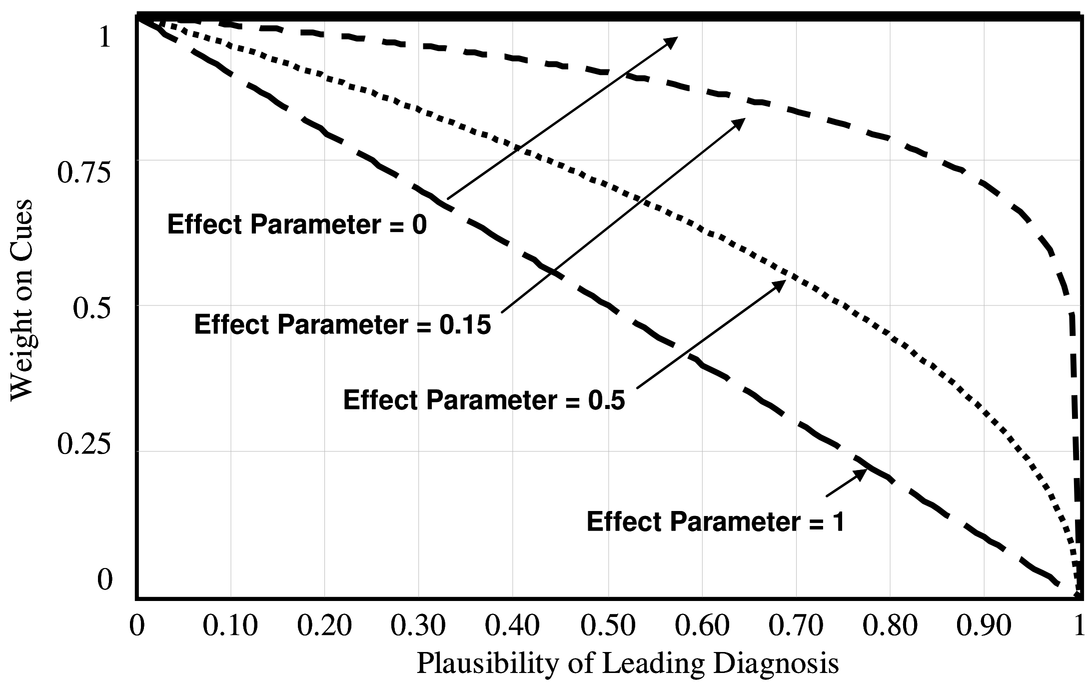
APPENDIX A

Figure A-1
Weight on Cues as a Function of Plausibility of Leading Diagnosis
for Various Settings of Effect of Plausibility on Weights



APPENDIX B

Integral equations are written in this appendix using the following notation:
Stock= INTEG (Inflow-Outflow, Initial Value of Stock), where the INTEG function means the integral from time 0 to time *t* (the current time) of the inflows less the outflows plus the initial value of the stock. The model is simulated using Vensim DSS software, available from www.vensim.com.

Equations for the Acting Subsection (Figure 1):

Algorithm Steps Completed= INTEG (Advancing the Algorithm-Resetting Algorithm ,0)
Units: Dimensionless

Advancing the Algorithm=(1-Algorithm Steps Completed)/Time Needed to Advance Algorithm
Units: Dimensionless/Minute

Time Needed to Advance Algorithm=8
Units: Minute

Cues Available=(Starting Plausibility of Leading Diagnosis+Algorithm Steps Completed*(Accuracy of Leading Diagnosis- Starting Plausibility of Leading Diagnosis))
Units: Dimensionless

Accuracy of Leading Diagnosis=IF THEN ELSE(Current Diagnosis=True Diagnosis, 1, 0)
Units: Dimensionless

True Diagnosis=4
Units: Dimensionless

Equations for the Interpreting Subsection (Figures 2 and 3):

Plausibility of Leading Diagnosis= INTEG (Updating +Carry Over to Leading -Resetting Leading, Initial Plausibility)
Units: Dimensionless

Updating=(Plausibility from New Cues-Plausibility of Leading Diagnosis)/Time to Needed Update
Units: Dimensionless /Minute

Plausibility from New Cues=Cues Available*Weight on Cues+(1-Weight on Cues)
Units: Dimensionless

Time to Needed Update=2
Units: Minute

Weight on Cues=(1-Plausibility of Leading Diagnosis)^Effect of Plausibility on Weights
Units: Dimensionless

Effect of Plausibility on Weights=0.5
Units: Dimensionless

Equations for the Cultivating Alternatives Subsection (Figure 4)

Plausibility of Alternative Diagnosis= INTEG (Cultivating-Resetting Alternative,0)
Units: Dimensionless

Cultivating=Effect of Plausiblity on Alternative*(1-Plausibility of Alternative Diagnosis)/Time Needed to Cultivate
Units: Dimensionless/Minute

Effect of Plausiblity on Alternative=min(1,2-2*Plausibility of Leading Diagnosis)
Units: Dimensionless

Time Needed to Cultivate=4
Units: Minute

Equations for Switching Diagnoses (Figure 5):

Change Trigger=IF THEN ELSE(Plausibility of Leading Diagnosis<Plausibility of Alternative Diagnosis, 1, 0)/TIME STEP
Units: Dimensionless/Minute

Resetting Algorithm=Algorithm Steps Completed*Change Trigger
Units: Dimensionless/Minute

Resetting Leading=Plausibility of Leading Diagnosis*Change Trigger
Units: Dimensionless/Minute

Carry Over to Leading=Resetting Alternative
Units: Dimensionless/Minute

Resetting Alternative=Plausibility of Alternative Diagnosis*Change Trigger
Units: Dimensionless/Minute

Starting Plausibility of Leading Diagnosis = INTEG (New Plausibility-Resetting Starting Plausibility, Initial Plausibility)
Units: Dimensionless

New Plausibility=Resetting Alternative
Units: Dimensionless/Minute

Resetting Starting Plausibility=Change Trigger* Starting Plausibility of Leading Diagnosis
Units: Dimensionless/Minute

Initial Plausibility=0.5
Units: Dimensionless

Current Diagnosis= INTEG (Diagnosis Counter,1)
Units: Dimensionless

Diagnosis Counter=Change Trigger
Units: Dimensionless/Minute

FIGURES

Figure 1
The basic stock and flow structure of advancing the algorithm

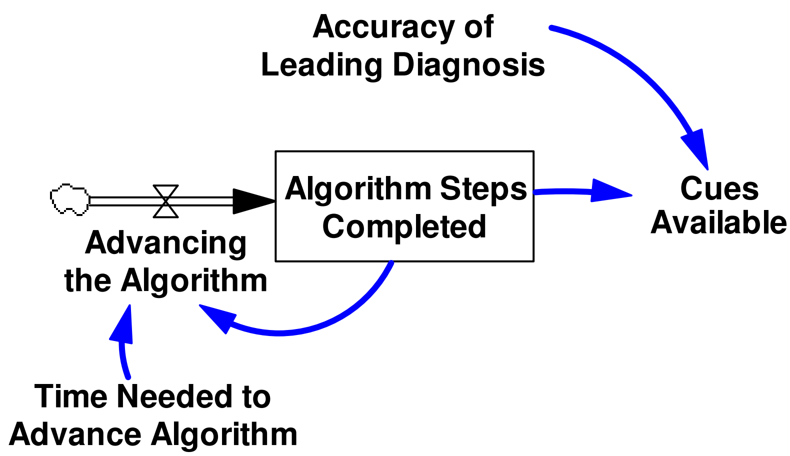


Figure 2
Updating the plausibility of leading diagnosis

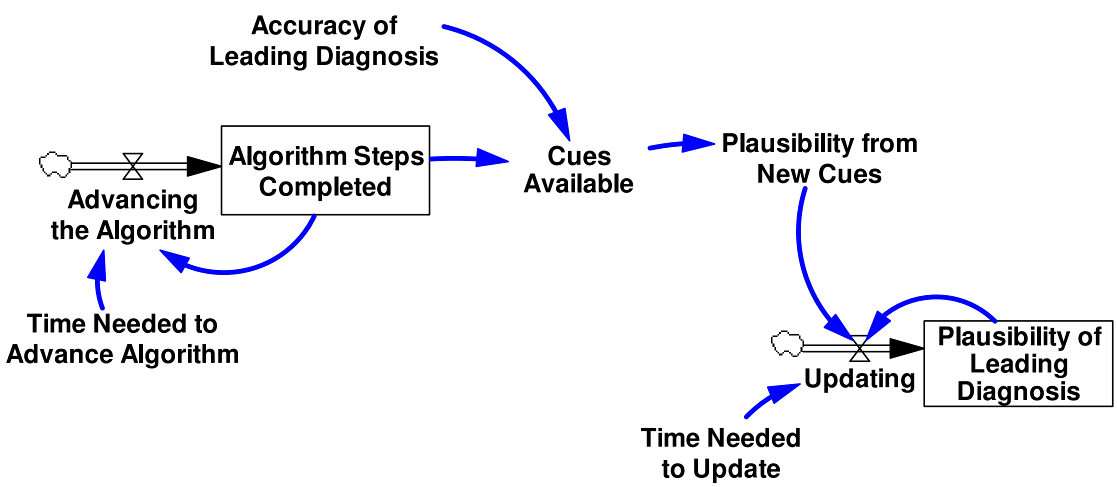


Figure 3
Feedback structure of Self-fulfilling interpretation

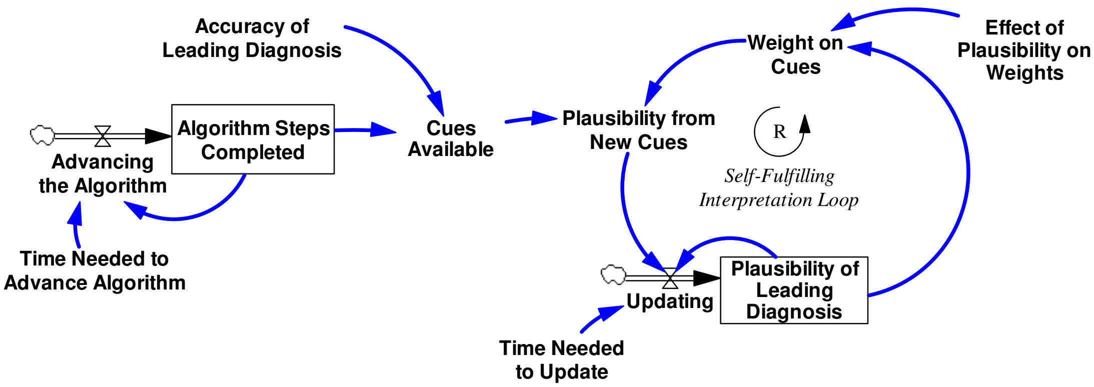


Figure 4
Core model structure showing the interaction of acting, interpreting, and cultivating alternatives

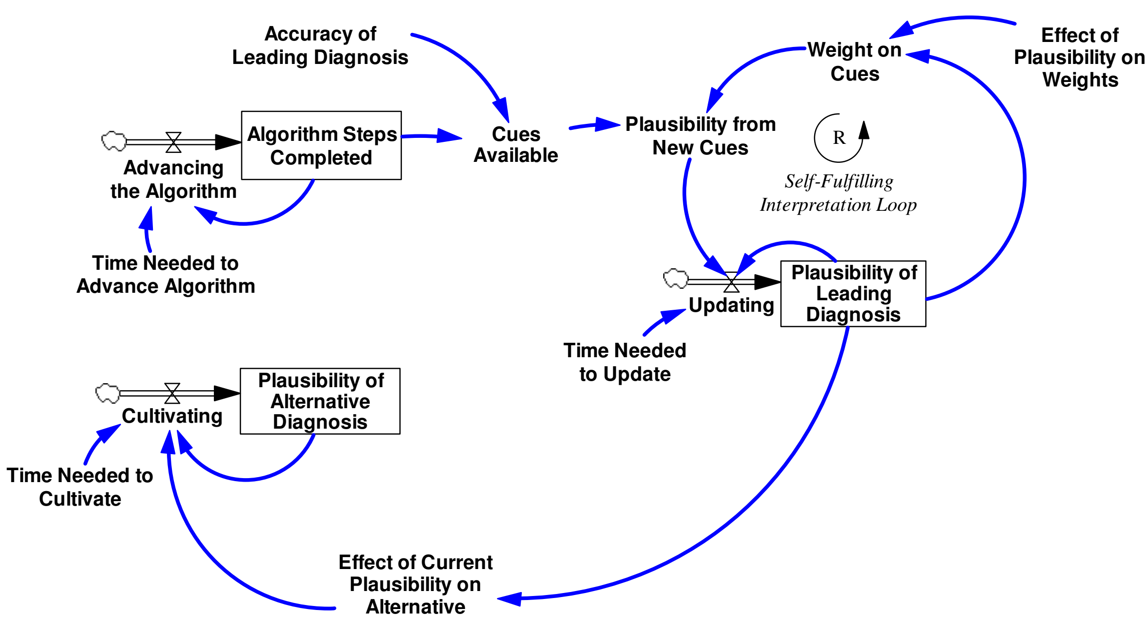


Figure 5
Changes to reset the model when the alternative diagnosis becomes the leading diagnosis

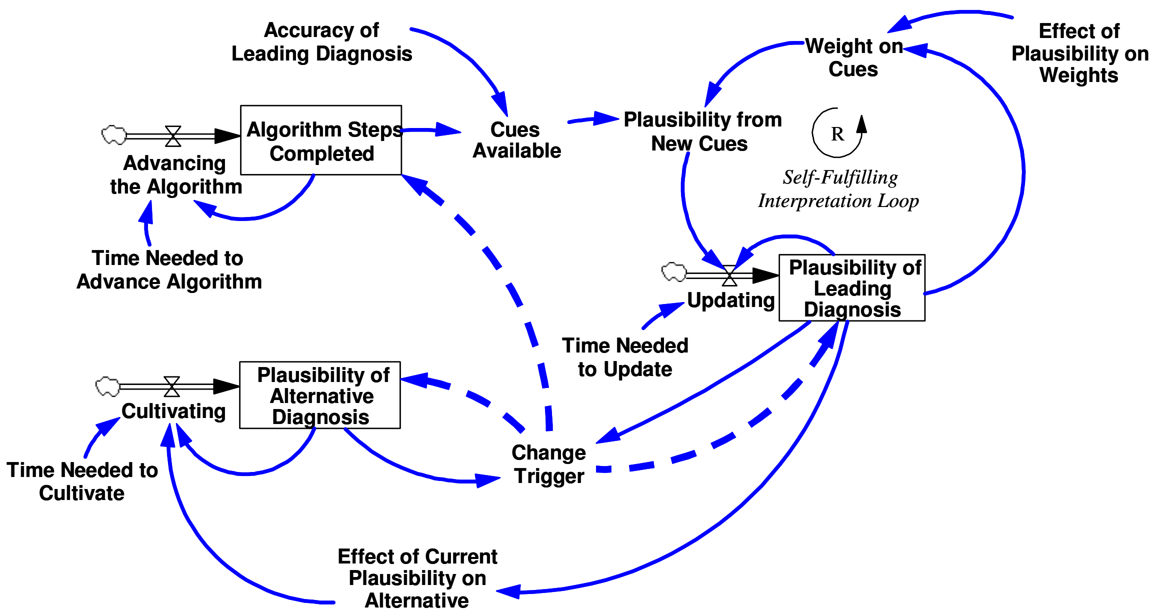


Figure 6
Adaptive Sensemaking: Discovering the correct diagnosis

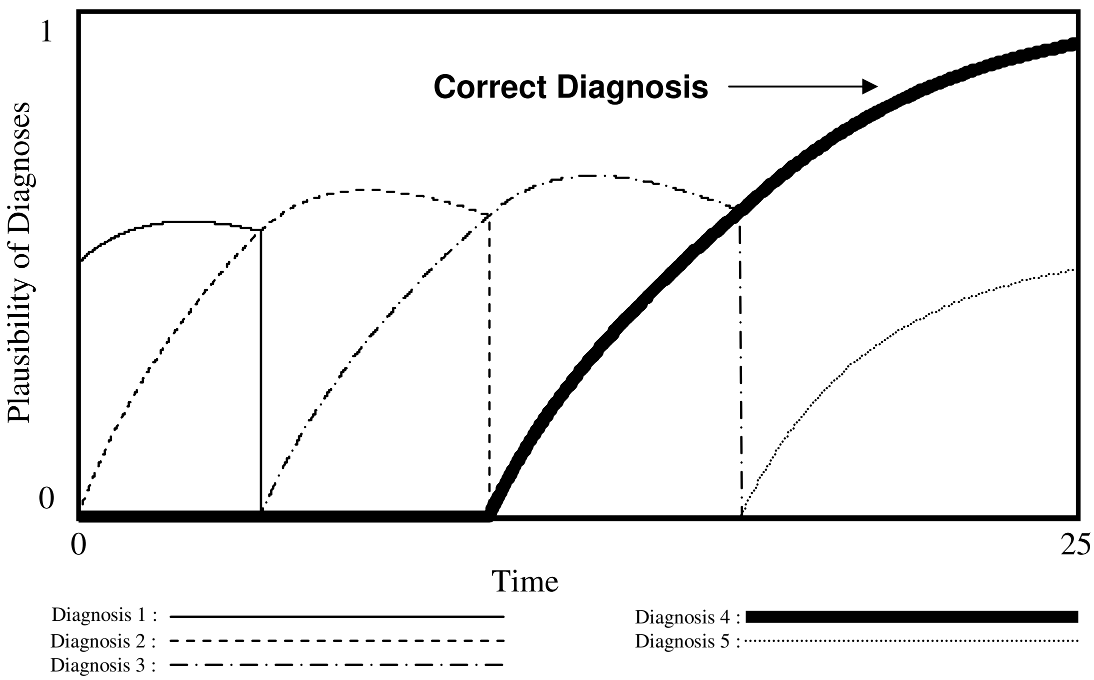


Figure 7
Fixating on an incorrect leading diagnosis

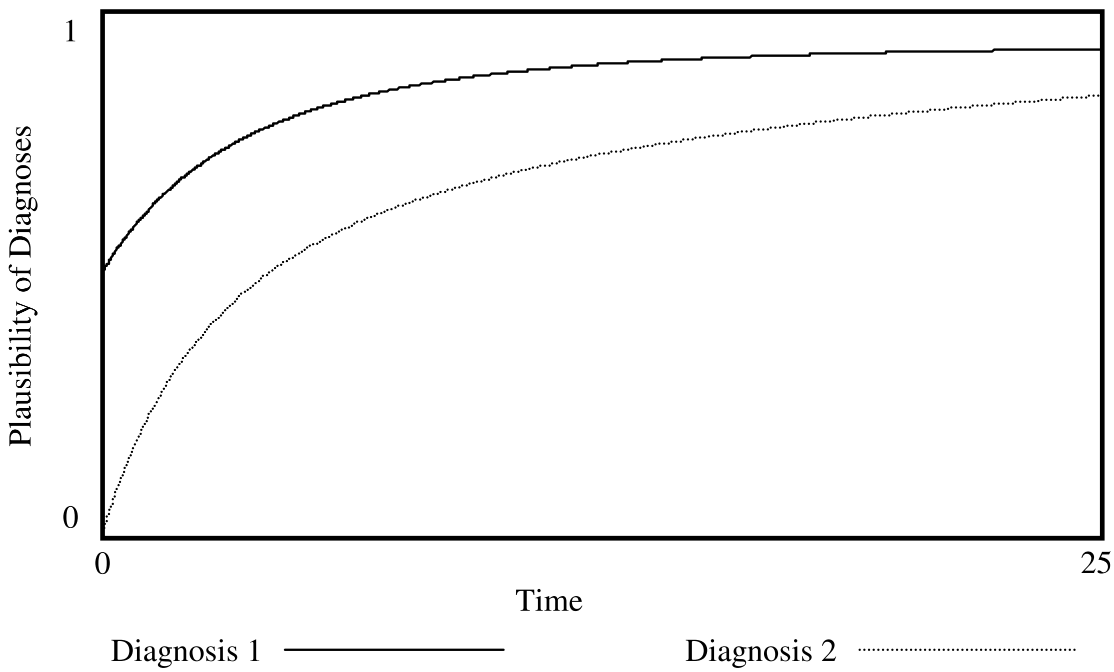


Figure 8
Diagnostic Vagabonding: Rejecting the correct diagnosis

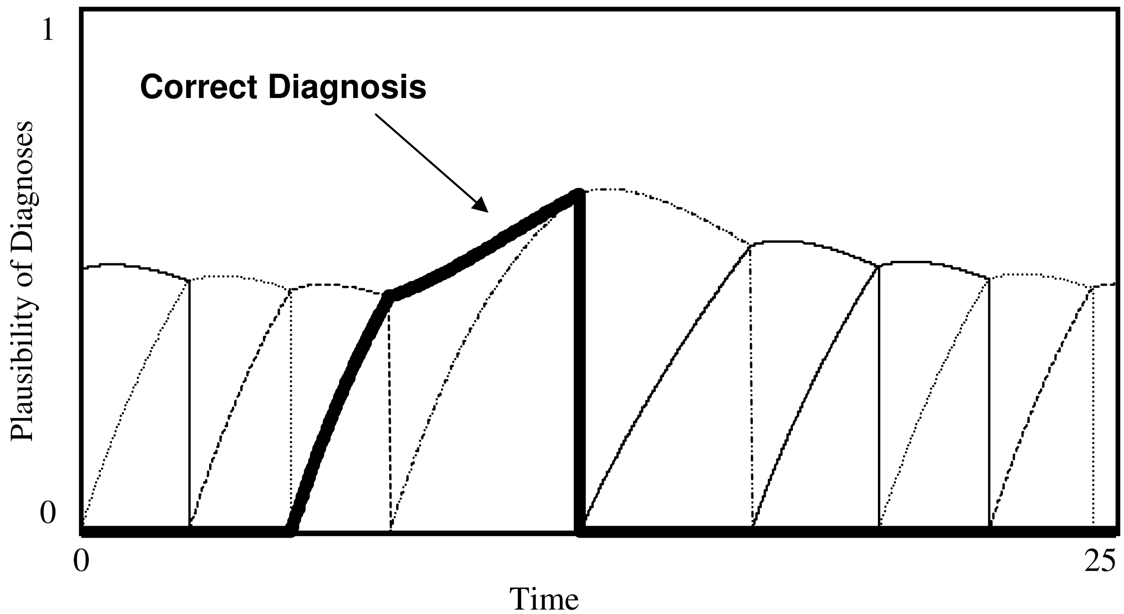


Figure 9
Sensitivity analysis showing system behavior for various rates of advancing the algorithm

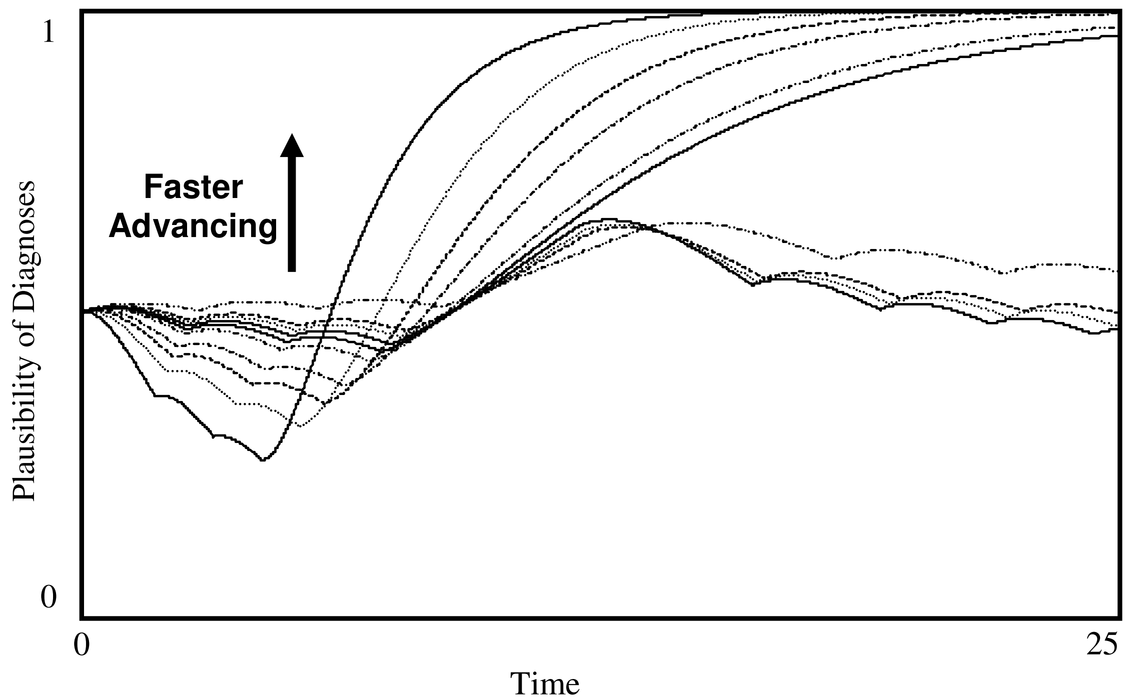


Figure 10

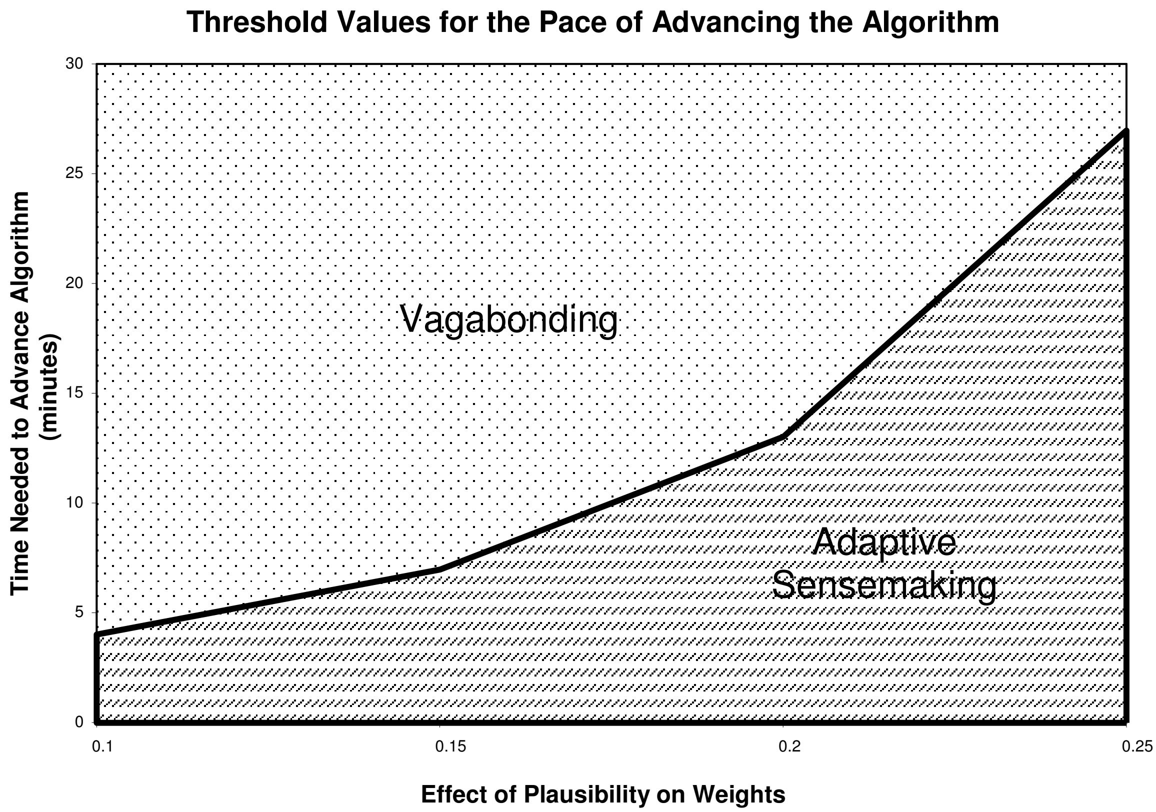

Threshold Values for the Pace of Advancing the Algorithm
Time Needed to Advance Algorithm (minutes)
30
25
20
15
10
5
0
Vagabonding
Adaptive Sensemaking
0.1
0.15
0.2
0.25
Effect of Plausibility on Weights

Figure 11

Threshold Values of the Pace of Advancing the Algorithm