Endogenous Human Behaviors in a Pneumonic Plague Simulation: Psychological & Behavioral Theories as Small "Generic" Models

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Abstract:

This report builds on a previous epidemiological model of a pneumonic plague outbreak that incorporated three behavioral responses as exogenous drivers and evaluated their importance in allowing us to replicate the actual outbreak (Heinbokel& Potash, ISDC-2003). The current paper describes our subsequent efforts to incorporate those critical and controlling behavioral dimensions into this model as critical feedback loops. We conceptually deconstructed the event into four segments: becoming aware of the outbreak, deciding to act in response, choosing a specific response, and returning to normal behavior. We utilized current psychological theories, such as the "Psychometric Paradigm" and "Brunswik's Lens Model," to build small, conceptually clear, transferable, and combinable behavioral submodels to simulate the first three segments involving information and social networks, social trust, and risk perceptions. We believe these modeling efforts comprise first steps in a critical process of translating current, frequently static, risk theories to dynamically responsive vehicles that can be flexibly and quantitatively applied to reliably aid in understanding and influencing responses to such public health threats, other extreme events, and other dynamic risk scenarios in general.

Background

At the 2003 ISDC meeting in New York, we first reported on an ongoing project exploring the feedbacks between a disease outbreak and non-linear human behavioral responses (Heinbokel and Potash, 2003). Using, as our test case, a September, 1994 outbreak of pneumonic plague in Surat, India, we were able to incorporate key events (behaviors), including the massive flight of about one-third the city's population within a 48 hour period, and a similar delay in distributing prophylactic antibiotics. What we discovered, and what we reported at that session, was a third behavior, a "freeze" response (as compared with the "flee" and "fight" behaviors described elsewhere) that involved self-quarantining (an average reduction by about 70% of original daily contacts), that needed to be incorporated into the model to accurately simulate what actually transpired.

While the value of the insight in demonstrating the power of and necessity to incorporate these "Three F" behaviors (fight, flee, freeze) into an epidemiological model of disease dynamics was not lost on our project's clients, our success generated a better and far more challenging question: "why" did people choose to act in particular ways at particular times? Exogenously programming the model to effect behavioral choices – when to flee, fight, or freeze in the face of changing disease dynamic – posed no major modeling challenges. ENDOGENIZING those behaviors – effectively understanding and simulating how and why they arose – was another story.

Overview

In moving into the second year of the project (Phase 2), we activated a mental model (Figure 1) that portrayed these responses emerging from a combination of information flows (or cues) that affected the population's perceptions of risk which, in turn, led to observable behaviors that fed back to affect the disease dynamic itself. In effect, by closing these feedback loops, the model could expand our collective understanding of a particular situation to permit more generic extrapolation to other communities, other diseases, and perhaps even to a broader range of risks.

Unlike the traditional epidemiological **S**(usceptible)-**E**(xposed)-I(nfective)-**R**(emoved) model, however, we undertook this task without a generally accepted model for structuring social behaviors. We solicited experts with prior background in social psychology, public policy, group behaviors, and "extreme events" to introduce us to a subset of the theories and scholarly literature they deemed most likely to inform our modeling. From an extensive and growing literature on judgment and decision-making, they focused our attention on the subjective nature of risk perception.

Two theories were particularly helpful. The "psychometric paradigm" provides a tool for scaling risk perceptions (Fischhoff et al, 1978; Slovic et al, 1980). This approach uses various quantifiable, "psychophysical" scaling and multivariate analytical techniques to argue that factors affecting risk perception can be organized into two broad categories that account for a wide range of perceived risk. These factors and categories effectively transcend cultural biases or particular types of hazards. The first category, labeled "Dread," incorporates a total of ten factors that define, on 1 to 7 scales, perceived concern about the severity of consequences, the

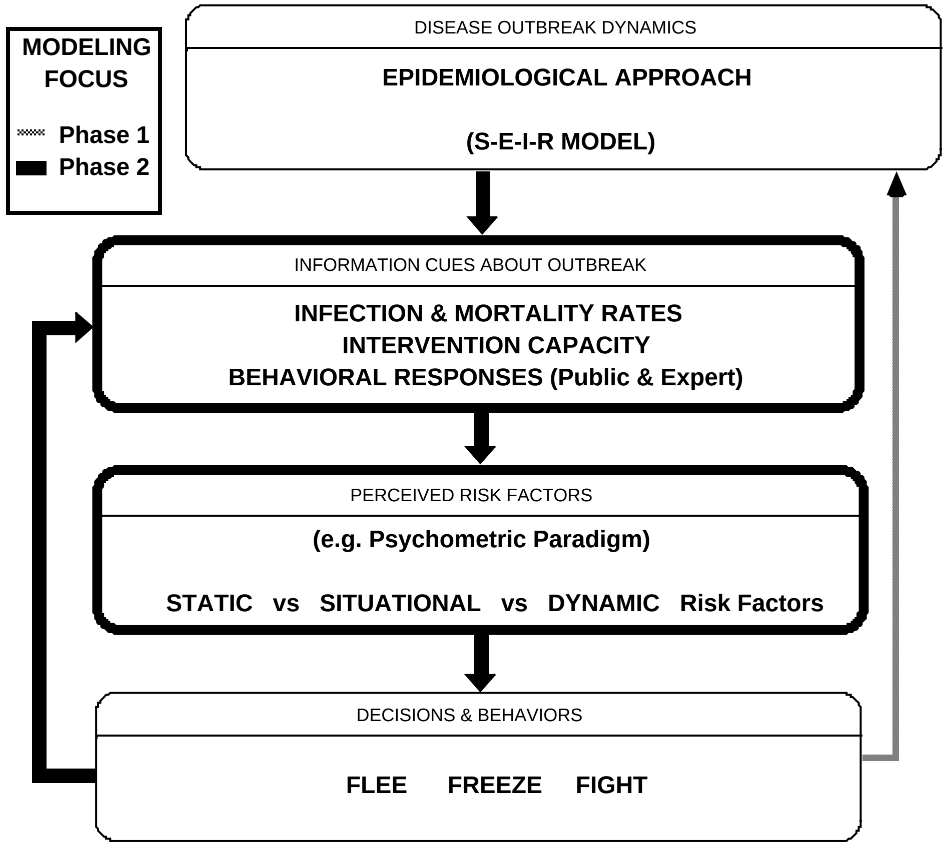

Figure 1: Overview of the feedback loop structure used in this description of human behavior and epidemic disease transmission. The upper sector represents a traditional S-E-I-R compartment model of pneumonic plague. The bottom sector and the right hand link represent Phase 1 of our project where we incorporated known behavioral responses to the disease as exogenous drivers influencing the progression of the outbreak (Heinbokel and Potash, 2003). The middle two sectors and the heavy links represent Phase 2 of the project where we developed an approach for defining those behaviors as functions of the disease itself. Information about the disease is transmitted to and filtered by the population, allowing them to determine their perceived level of risk from the disease. That level of perceived risk, in turn, influences behavioral responses (themselves a cue for further risk analyses), closing the feedback loop and bringing those decisions within the boundaries of the system as endogenous elements of those feedbacks. In this model we distinguished between "public" and "experts" (or well-informed caregivers). Figures in this paper may refer to one or the other population, although the structures for each subgroup are identical.

emotional reaction to the hazard (referred to as "dreadfulness") and the potential for controlling the negative consequences (or "controllability"). The second category, referred to as "Familiarity" (or "Unknown Risk"), incorporates elements of voluntariness, knowledge of the hazard, and the transparency with which its effects occur.

In addition, Brunwik's "Lens Model" of cognition (Brunswik, 1956) uses images of "cues" and "lenses" to distinguish the "true," but unknowable, state of an environment from multiple fallible perceptions that people construct by using personal lenses to select and weight available information ("cues"). While the rigors of the Brunswikian testing regime render it beyond our means to model (most work, to date, focuses on differences in individual decision-making (e.g. Hammond, 2000), the concept of a limited number of weighted, dynamic "cues" that capture the "dread" and "familiarity" measures is a powerful one that is within our means to operationalize.

These theories offered a foundation for developing conceptual maps (and subsequent simulations) that more tightly and mutually link disease and behavioral dynamics. Additional discussions with the experts suggested four discrete and sequential considerations (decisions) required to define behavioral responses to evolving "extreme events" such as the Surat outbreak (Figure 2). Those four responsive stages (flows) are:

1. Recognize Risk
2. Recognize Need to Act
3. Choose and Implement an Action
4. Return to Normality (essentially ignored given the short time-line of our specific modeling charge)

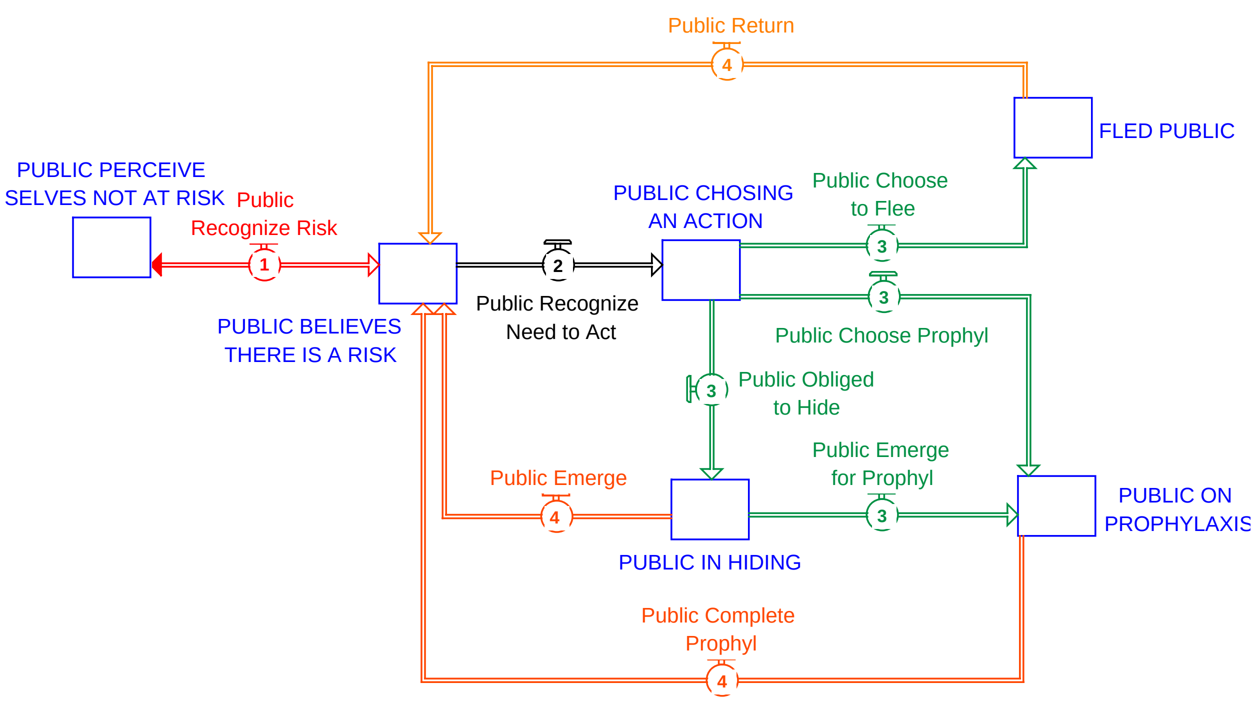

Figure 2: Concept Map of Primary Social Behaviors Exhibited During a Pneumonic Plague Outbreak

Having recognized these stages, the challenge then focused on identifying and converting these, and additional, current theories to usable simulations that could be incorporated as discrete and transferable elements of this larger model. That process forms the basis for the remainder of this paper.

Flow 1: Recognize Risk

Flow 1 ("Recognize Risk") focuses on risk communications. People not only need to "hear" of the outbreak but also to believe that it represents a personally significant situation. Information flows through three pathways, informally (word of mouth), or formally via the media or the authorities (Kasperson et al, 2004). Such multiple pathways create possibly conflicting messages to be sorted and weighed. The relative credibility of any source depends on "trust." Informal exchanges between acquaintances carry, on average, higher levels of trust than formal communications. "Social trust," i..e. people's confidence in the accuracy of information received from a given source, provides a lens through which that information is evaluated (Frewer, 2004). Relatively small models 1) of informal information diffusion competing with formal communications and 2) of the lens of social trust provide the basic logic and structure for defining this first flow of risk recognition.

The basic structures, presented below, form the basis for the model's definition of how people receive and process information about the existence of a disease outbreak. The structure in Figure 3 has at its core the dissemination of information that serves to move people from a position of ignorance to one of knowledge. That process can be mediated by: 1) formal

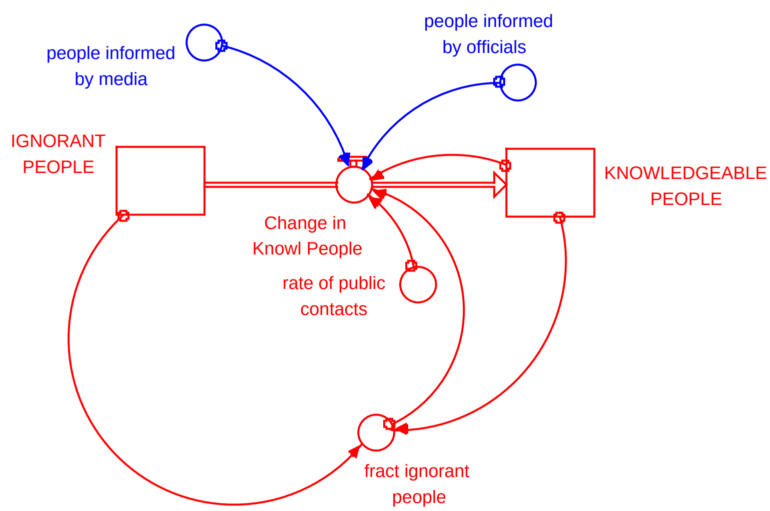

Figure 3: Formal (above the flow) and Informal (below the flow) Information Pathways.

communications, from public officials and/or the media; those are delivered at particular points in time to targeted populations (structure above the stock and flow of Figure 3); and 2) informal communications (below stocks and flow), involving social networks; those are driven by the intensity of the message and, more importantly, through an infectious "rumor mill" dynamic.

The person-to-person nature of this spread has potential for explosive spread, based on an ever-growing population spreading the message.

Figure 4 identifies another critical component in the flow of information that pertains to the processing and evaluation of multiple streams of information (here one source of information emanates from public officials while the second reflects the news "on the street"). These streams may well present contradictory or at least inconsistent messages. In such cases, the nature of PEOPLE'S TRUST IN OFFICIAL CREDIBILITY (a stock that is dynamic over time), combines with the magnitude of the difference in message contents to affect which information people choose to believe. What is critical in the unfolding dynamics of a multitude of events where public officials compete with other information sources is the changing nature of people's trust and its subsequent impact on what they choose to "hear" or not. The theory of "social trust," captured in this model, illustrates the "asymmetry principle" where trust can dissipate far more quickly than it can be regenerated or bolstered. The nonlinear nature of changing public attitudes involving social trust (Figure 4), when combined with similar nonlinear patterns of information flow (Figure 3), can generate non-intuitive flows of "new" people who "recognize risk" in Flow 1.

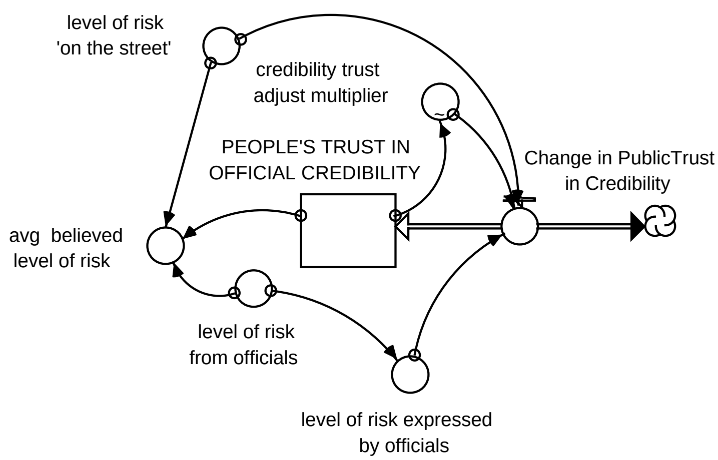

Figure 4: Social Trust as a Determinant of the Level of Perceived Risk in the Face of Multiple Streams of Information

Flow 2: Recognize Need to Act

Once believing in a credible risk, individuals must determine whether that risk is sufficient to warrant a behavioral response. Flow 2 ("Recognize Need to Act") uses a modified "psychometric paradigm" to scale recognized "Risk factors" that measure perceived risk. Normally the psychometric paradigm groups risk factors into "familiarity" and "dread" categories, based on static representation of an event (Fischhoff et al, 1979). Moving beyond that norm in the risk field and focusing, as this model does, on a dynamically *changing* event, we regrouped the outbreak's risk factors into three categories: "static," "situational," and "dynamic." Those designated as "static" and "situational" factors remain constant in any given scenario. Most important in this model are a third set, our so-called "dynamic" factors that we believe would change as the disease situation evolved in a given outbreak. They address 1) perceived or projected likelihood of infection (the “Individual vs Catastrophic” factor in the published psychometric literature); 2) perceived likelihood of mortality (“Fatal vs Non-fatal” factor in the literature), including the overall mortality rate (victims die vs recover) and (3) the “personalization” of mortality (based on social networks that recognize varying degrees of “connection” with victims).

When modeling the changing perceived risks of infection (Figure 5) or mortality (Figure 6), we have worked on the basis that for each risk factor both the absolute values of the perceived risk and its trajectory (or direction and rate of change of those parameters) will affect the population’s views, hence maintaining in the model a memory of past values. Scholarship indicates, as well, that there are several differences between the “experts” charged with managing the disease and the public at large. Experts process change in smaller increments (that is, they have more ready access to information and greater desire to frequently update their knowledge of what is happening) and are likelier, understanding disease dynamics, to predict anticipated change through exponential projections.

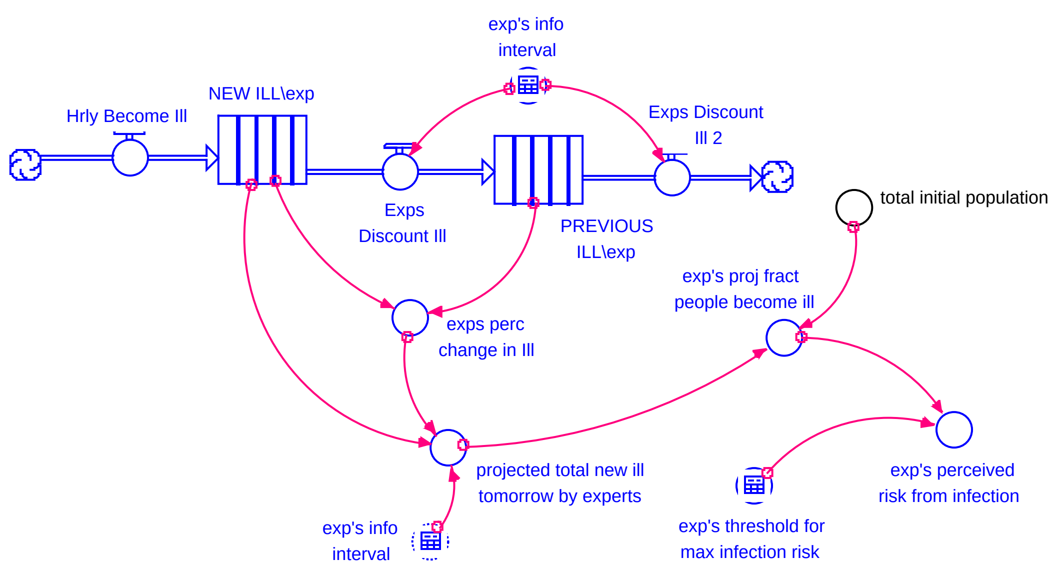

Figure 5: Defining perceived risk from infection. Comparison of the present cases (NEW ILL) with the comparable number from the recent past (PREVIOUS ILL) provides a measure of “change” in the situation: better or worse, rapid change or slow. That rate of change is then projected into the future, either through a linear projection (by the “public”) or an exponential one (by “experts”), to estimate a likely number of individuals to be affected over some future interval of time. That in turn generates a sense of “risk” from this factor of the scenario.

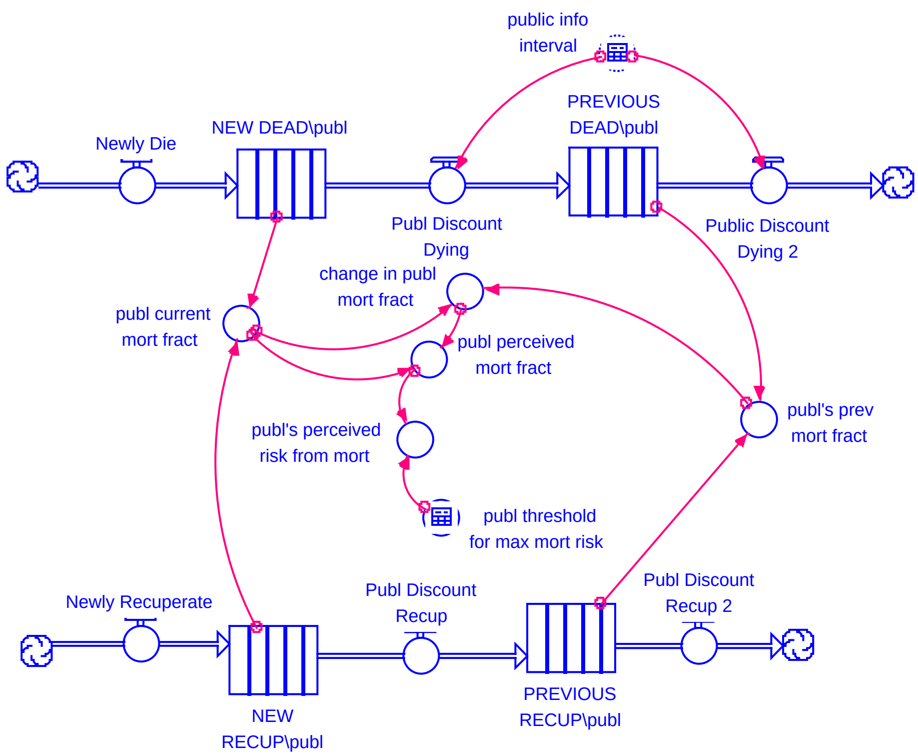

Figure 6: Defining perceived risk from mortality. Comparison of the recent deaths (NEW DEAD) with the comparable number from the recent past (PREVIOUS DEAD), both as absolute numbers, but also as a fraction of the total case resolutions (requiring knowledge of recuperations), provides a measure of "change" in the situation: better or worse, rapid change or slow. That rate of change is then projected into the future, either through a linear projection (by the "public") or an exponential one (by "experts"), to estimate a likely number of individuals to die over some future interval of time. That in turn generates a sense of "risk" from this factor of the scenario.

In addition to processing differently, the public, in particular, is subject to "personalizing" risks (Figure 7), based on a personal awareness of someone who has died from the disease. Such a social network, like the earlier information flow, depends on a person-to-person spread of information that is implied in the "avg # who personalize a death" element of the model.

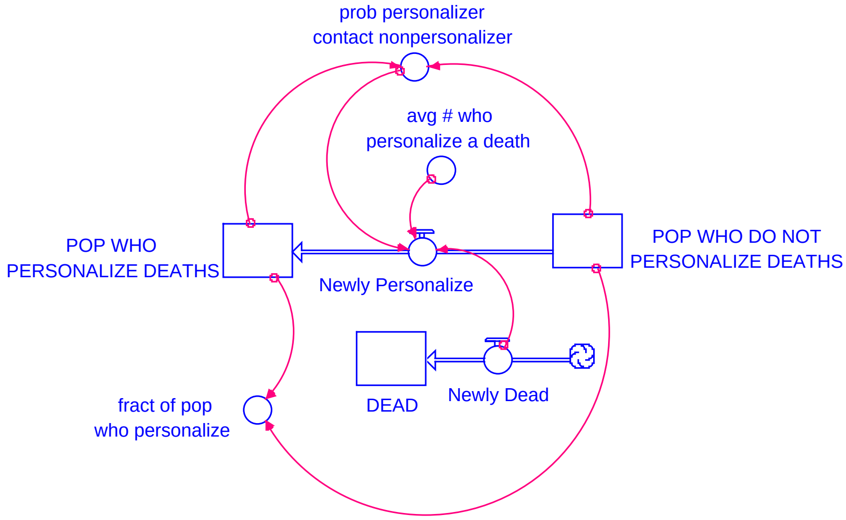

Figure 7: "Personalizing" Deaths. The deaths of people who are close to us in our social network have a greater impact than would the death of strangers. Depending on the strength of the social network (a given death personally affects how many others?) each death will generate, through word of mouth communication, a number of individuals for whom the outbreak now has a personal connection.

Finally, the actual measure of dynamic perceived risk incorporates risk projections (on infection and death) with any impact of personalization. These are weighted to calculate a "total perceived risk from dynamic factors." That is then added to the static and situation risk perceptions to derive a "total avg perceived risk." NOTE: the weighting of the risk factors, in addition to the actual perceived risks are likely to differ between the expert and the public subgroups.

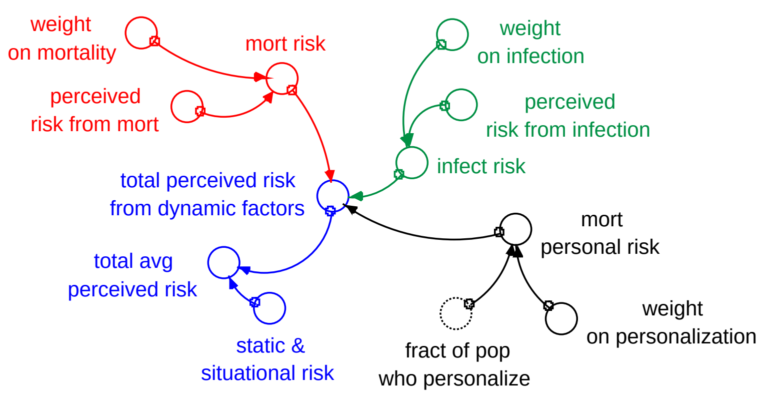

Figure 8: Measuring risk perceptions through the use of a psychometric paradigm approach that utilizes a re-sorting of the typical risk categories into three classes: "static," "situational," and "dynamic."

Flows 3: Choosing an Action

Once motivated to act, people chose between three actions (fight, flee, or freeze, in the flows numbered "3" of Figure 2). Again, behavioral choices are evaluated using a combination of "cues" and "lenses" that continue to include perceptions of infection and mortality dynamics, as well as a new measure of "trust" in the authority's capacity (and later, as the event unfolds, of their realized track record) to control the disease. There are few studies or theories on effects of changing conditions driving behavioral choices. We developed this portion of the model with the help of expert consultants using the following logic. People who have decided to respond (those in the "CHOOSING AN ACTION" stock of Figure 2) make a first choice: to seek (and trust) the community's medical resources to prevent or treat the disease or, alternatively, to flee. Should either primary choice be blocked by social, economic, or logistical constraints, self-quarantine ("freeze") would be utilized.

The decision tree depicted below (Figure 9) controls the behavioral dynamics. "New" people enter this phase having recognized a need to act and being prepared to choose a behavior (accumulating in the "PEOPLE HAVE CHOSEN TO ACT" stock).

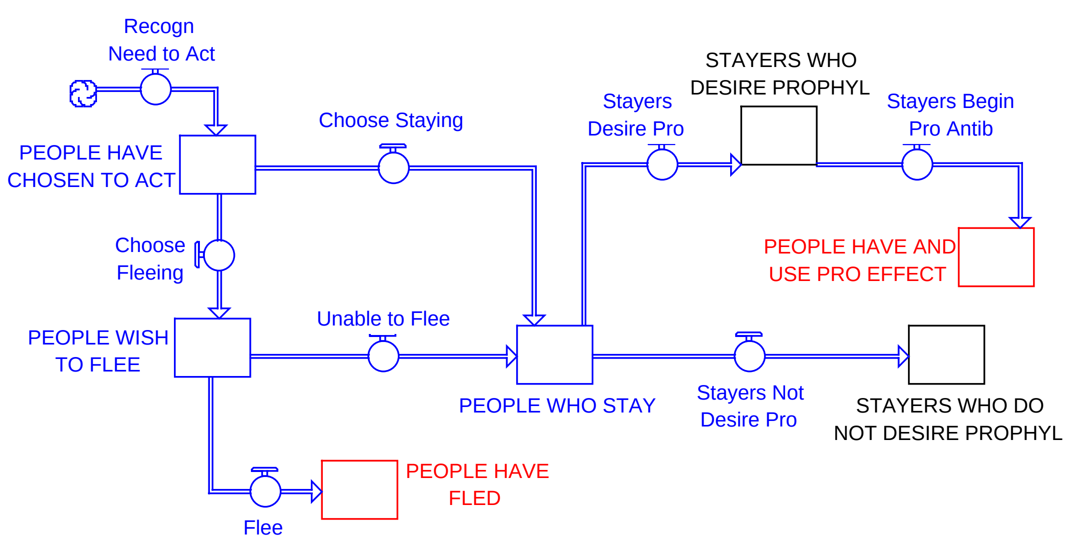

Figure 9: Basic Stock/Flow Structure Relating to Behavioral Response. Once people have decided that some action is required (become motivated), we theorize that they work through a simple and rapid set of decisions: Do I wish to stay or flee? If the latter, am I constrained to stay? If I stay, do I desire prophylactic antibiotics? If so, can I get them? When all other desired actions fail, the remaining motivated population will engage in some isolating or hiding activity to reduce their contact with others.

Their first choice or decision is to determine if fleeing the community is warranted. This is certainly a more complex individual decision than we are able to depict here, but recall that in the face of extreme events, relatively little time for careful thought may be available. We begin with an assumption that there is a basic level of predisposition within the members of any community to flee in the face of danger (the initial value of the stock in Figure 10). Depending on the pressures brought to bear and the characteristics of the population, that initial value could change dynamically as the threat waxes and wanes. That disposition, as shown in Figure 10, influence the fraction of motivated people who choose fleeing as their favored behavioral response (the role of that "flee disposition adjust multiplier" is realized in regulating the flows in Figure 9, although that level of detail is not shown in Figure 9).

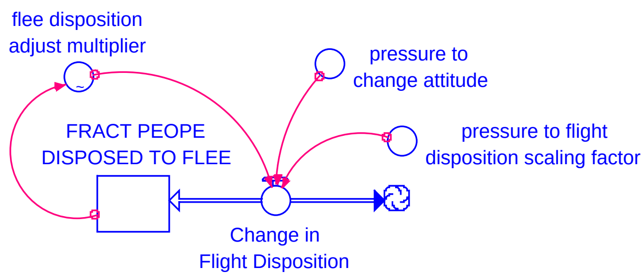

Figure 10: Dynamics of Disposition for Flight. Again, there may be differences in how the expert and public portions of the population respond in this sector of the overall model.

In addition, there is an important measure of social trust in the community officials' ability to manage the outbreak (Figure 11). That TRUST begins at some characteristic level and can grow or shrink based largely on how the outbreak progresses. If the situation is worsening, TRUST will be drained; if the situation is improving, then TRUST will grow. The level of that TRUST will influence the rate at which people choose to accept the officials' offer of prophylactic antibiotics. Again, the influence of this consideration is not explicitly shown in Figure 9.

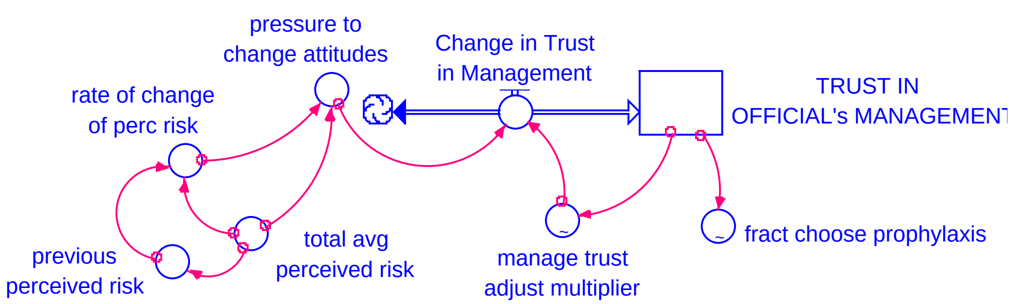

Figure 11: Social Trust in Officials' Ability to Manage Event. The dynamics are outlined in the text above.

The structures, then, in Figures 10 and 11, drive people to weigh the two basic choices: to stay (or to leave) and to seek prophylactic antibiotics (or not). Those trusting the officials' ability to manage are disposed to stay and to accept the antibiotics. As the event unfolds, however, rates of social trust may change leading in turn to changes in dispositions to flee and to accept drugs.

It must be understood, however, that the issue of hiding remains. Returning to Figure 9, those who hide comprise two populations: those who stay (whether by choice or constraint) but do not desire antibiotics and those who stay but who cannot obtain the antibiotics they desire. For those, the option of "hiding" is the best available alternative. Those individuals may, as the figure suggests, modify their decisions as events unfold and new opportunities present themselves.

Model Output For Surat:

The structures described in this paper have been assembled and used to drive what were the exogenous behaviors contained in the original model. This "new" model has been tested again against the known facts of the Surat, India, event to determine how well it can project the likely disease dynamics arising out of these behavioral decisions. Incorporating the same epidemiological data of that outbreak together with information on where and when antibiotics were administered (this model cannot predict medical policies or capacities), this model generates a reasonable "curve fit" with the actual data for hourly rates of new infection (Figure 12) as well as total cases (Figure 13) of pneumonic plague in the September 1994 scenario.

But what about the simulated behaviors? Does the new model endogenously generate individual behaviors that match what actually happened in Surat? The model generates the flight of over 200,000 residents (a figure lower than that exogenously programmed into the first model); in addition, the model projects a figure of nearly 200,000 effectively using antibiotics as they became available (interestingly, that is a figure closer to the small fraction hypothesized on the basis of his post-epidemic interviews than to that used in our earlier modeling) (Shah, 1997). Finally, over 600,000 or more than 40% of the population, went into hiding and reduced their contacts by 90%.

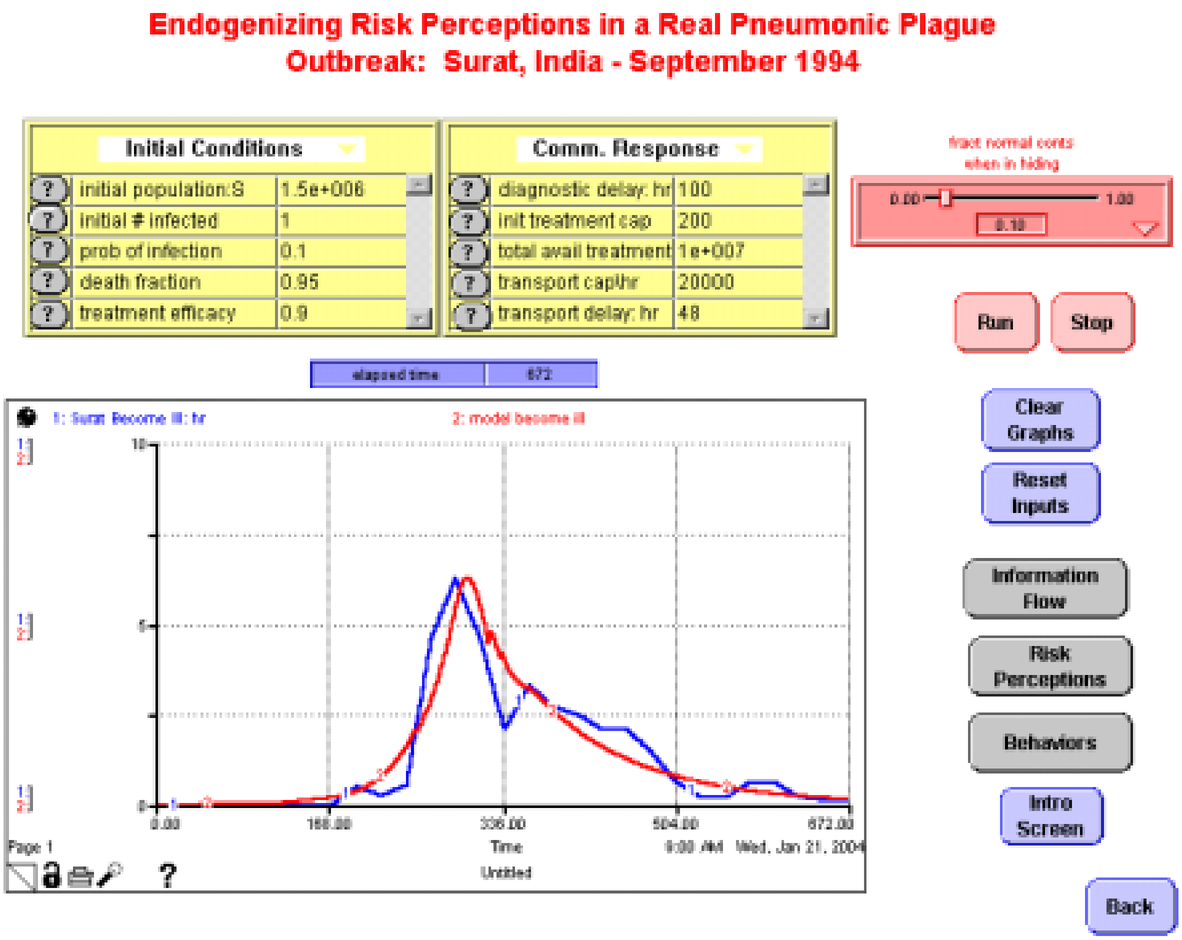

Figure 12: “New” model output vs actual numbers -- new hourly infections in Surat.

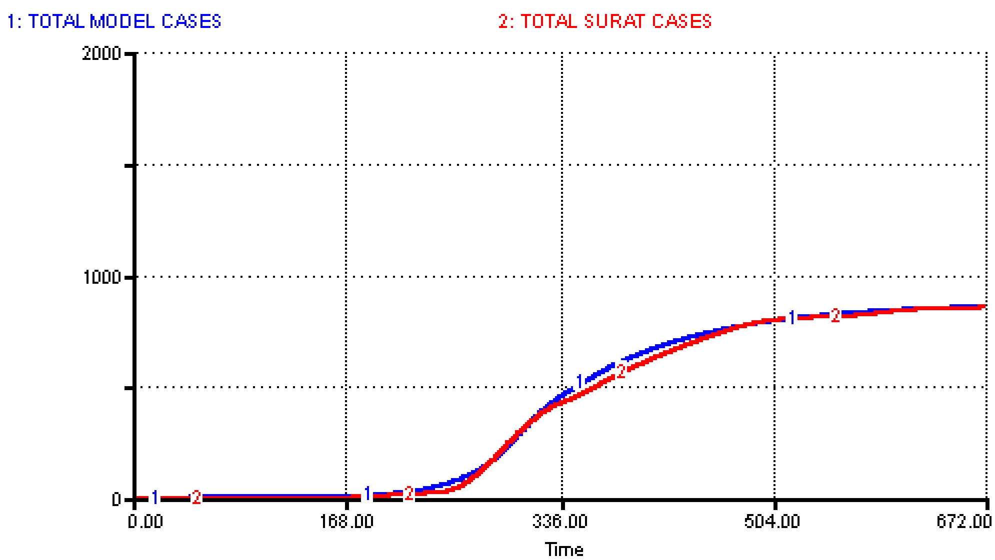

Figure 13: “New” model output vs actual numbers-- the cumulative total number of infections in Surat.

Summary

The intent of building this model was not primarily to replicate the past experience of a single outbreak. Rather we sought to test the applicability of selected psychological theories on human behavior within the rigid requirements of model construction and simulation. We developed a set of small, generic models of specific portions of the sequence through which individuals learn of such a risk, determine whether a behavioral response is necessary, and then choose an appropriate option. These models are first steps in a critical process of translating current risk theories from their frequently static orientation to dynamically responsive vehicles that can be flexibly and quantitatively applied to reliably aid in understanding and influencing our responses to such significant public health threats, to other extreme events, and to risks in general.

The small submodels or psychological kernels (Figure 14) we have identified and incorporated into this model are, perhaps in retrospect, collectively more valuable than the sum of their integrated parts. These theories do not simply apply to the singularity of an Indian pneumonic plague outbreak, but should find practical applicability in studying a variety of other dynamic events.

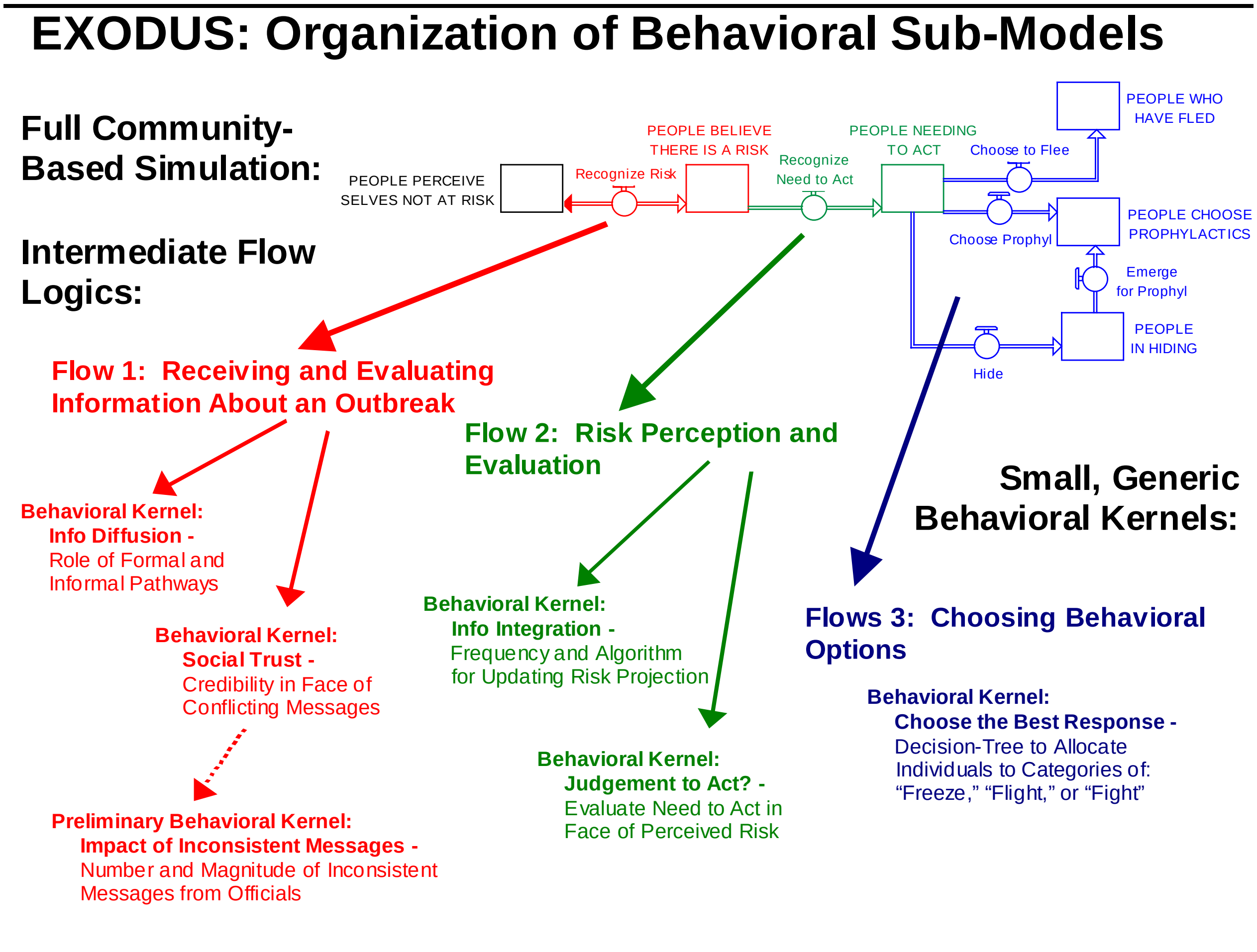

Figure 14: Summary of the small psychological models constructed to allow human behaviors to be incorporated endogenously into a computer simulation of an outbreak of pneumonic plague.

Information and social networks, social trust, and risk perceptions are very much critical components of other events including, but not limited to, a wide range of extreme events. The challenge, we submit, is to contemplate how and where these small models can be used, individually or in combination with other (as yet unbuilt) models, to allow further examination of those other events.

We strongly suggest that this preliminary effort demonstrates significant "value-added" for undertaking to model such psychological or behavioral theories. Such early efforts are more likely to identify theory shortfalls and limitations than to generate breakthrough insights. That will prove extremely positive, however. Historians of science will recall, in the great scientific breakthroughs of the past, that the literature largely consisted of pointing out how and where failures had occurred. If we are to move toward developing better models, it behooves us to recognize the great distance we need to cover.

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