# Human Systems and Complexity

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## A Provocation

We often speak of individuals and groups as being acted on by external "forces." I suspect we use the word force, borrowed from the language of physics, to illustrate that environmental factors such as technology, work, and politics appear to produce certain responses in people. Just as mechanical forces act on physical systems, there are forces which act on "human systems"–this is simply a logic of cause and effect. In helping make sense of how humans respond in different situations, these intuitive models are used to aid in decision making. Whether these decisions are political (introducing a new policy) or personal (choosing how to spend your time), we use informal mental models of the world to assess the consequences of taking certain actions. In physics and engineering, models are used to avoid costly experiments. Similarly, people use mental models to avoid a trial and error–we can experiment with different possible worlds in our imaginations, and take the actions which seem likely to lead to the best outcomes.

A force applied to a mass-spring-damper system causes the system to change state via motion of the mass. Analogously, we will consider a changing environment as a force which causes human systems to change "state." Unlike the mechanical system, it is not clear what a good measure of the state of a human system is. But the notion of a state, however vague, is supported by our intuitions about these complex systems. It is obvious that changes in the environment cause *some* change in people, even if it is hard to pinpoint or quantify what precisely is changing. Do occurrences like the advent of large language models, war in Ukraine, or starting/finishing college affect you? If so, then you have already have some notion of a state. *As an experiment, what if we take this analogy even further?* Perhaps we might write

$$s(t) = G\Big(f(t)\Big)$$

This relation is intended to mean "the state of a person in time $s(t)$ is a function $G(\cdot)$ of time-varying external forces $f(t)$."[1] Again, we do not necessarily need to have clear understanding of how a state $s(t)$ is measured, and

[1] $G(\cdot)$ is technically an operator as it maps from one space of functions to another.

certainly not precise knowledge of the function $G(\cdot)$ which relates the human state to external forces. Forces are perhaps easier to understand, as they are conceptualized as things in the environment which may have an influence on individuals or groups. At this point, the idea is to cast an existing qualitative way of thinking about human systems into a general mathematical framework and see where it takes us.[2] It is often interesting and useful to model the time-dependent response of a system in physics or engineering, so we do the same here. The time dependence of our hypothetical model suggests that we care about the human response to a dynamic environment. For example, our technological environment is constantly changing and being disrupted–the present and future effects of this innovation are the subject of many books, articles, and discussions. Informal models of how society will respond in time to these emerging technologies are used in thinking through these questions. Thus, time dependent forces and states seem to be a reasonable framework for our model. See Figure 1 for a graphical depiction of this approach.

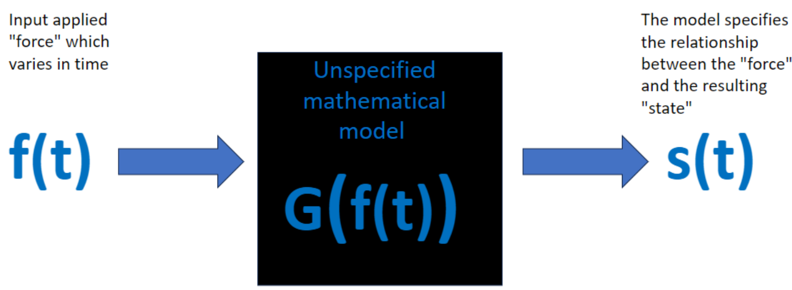



Figure 1: Schematic of a “human system.” Because it relates input forces to output states, we call $G(\cdot)$ a model.

## Exploring the Model

Now that we have established a general framework, we can use intuition about how we as individuals respond to influences from our environment to see what kind of properties the model should have. The first question we will ask of our hypothetical model is

$$\text{if } s_1(t) = G\Big(f(t)\Big) \quad \text{and} \quad s_2(t) = G\Big(cf(t)\Big)$$

[2]Economics is the field most interested in developing mathematical models of social systems. Some specific social phenomena of interest are: disease spread, rumor circulation, population growth, casualty in warfare, migration from one political party to another, and economic effects of climate change.

$$s_2(t) \stackrel{?}{=} cs_1(t)$$

for an arbitrary constant $c$. In words, this is asking: if we know the state produced by environmental influence $f(t)$, does multiplying that environmental influence multiply the output state in the same way? We are investigating *scaling* properties of the model. Let's consider an example: if the force $f$ is a measure of technology use, and the state $s$ is a measure of anxiety, does doubling the amount of technology use double anxiety? I would argue not necessarily. Intuitively, we might think that at low levels of technology, increasing technology use does not increase anxiety at all. Looking to the distant past, transitioning from the use of hand tools to simple machines might lower anxiety through facilitating manual labor. But when technology is more prevalent, doubling technology use might have a very different effect, possibly leading to a dramatic increase in anxiety. This is perhaps the case in an era of widespread digital technologies, where an hour or so of daily social media use may have no mental health impact, but multiple hours spent online each day may be psychologically harmful. Increasing technology use in the case of hand tools reduces anxiety, but in the case of digital technology, it increases. We have come up with a plausible counterexample to show that the scaling property should not hold in general. Thus, we can say the following

$$G\Big(cf(t)\Big) \neq cG\Big(f(t)\Big)$$

Without specifying precisely what $G(\cdot)$ is, we have learned something about its properties. It is interesting to note that we can establish some properties essentially by common sense. Now, as before, we will use existing intuition about human systems to ask another question of the model. We want to investigate the following:

$$\text{if} \quad s_1 = G\Big(f_1(t)\Big) \quad \text{and} \quad s_2 = G\Big(f_2(t)\Big)$$

$$G\Big(f_1(t) + f_2(t)\Big) \stackrel{?}{=} s_1 + s_2$$

In words, we want to determine if the combined effect of two forces is the sum of the responses to each force individually. Here, we are investigating *interaction* properties of the model. Again, we will try to think of a counterexample to demonstrate this property should not hold in general. This is a bit trickier than the scaling property. If $f_1$ measures the force associated with digital technologies, and $f_2$ that of political polarization, there is good reason to believe that an individual's response to these two forces is NOT simply the sum of the response to each force separately. In other words, digital technology and political polarization interact in some way to produce a new effect which cannot be decomposed into two distinct contributions.[3] This is equivalent to saying

[3] In making this argument, we are not being careful to consider the meaning of the time dependence of $f_1$ and $f_2$. To be more precise, we can think of these as measuring the evolution

that the response to the influence of digital technology depends on the level of political polarization, and conversely, the response to political polarization depends on the amount of digital technology. This seems fair to say in a world where the creation of and reaction to polarization is intimately intertwined with online media platforms. Thus, we can say that

$$G\Big(f_1(t) + f_2(t)\Big) \neq s_1 + s_2$$

Our model of the human response to environmental forces should account for the fact that these forces frequently interact with each other in meaningful ways. We cannot look at a human system's response to individual forces in isolation and expect to get the full picture.

It will perhaps be familiar to engineers that by investigating these scaling and interaction properties, we have shown that the the model $G(\cdot)$ is non-linear. Based on these simple thought experiments, it is clear that any model which seeks to capture human responses to external stimuli must be non-linear in order to be realistic. Whether or not such models can be built is not clear. All I claim is the following: *if a good model of this sort were built, it would have to be non-linear. Though it is not yet clear, we will see that this essentially guarantees these systems are highly complex.*[4]

# A Particular Non-linear System

Having argued that any realistic model of a human system must be non-linear in order to capture two intuitive properties, we can now explore the behavior of a particular model. I have invented this model as a potential description of the time evolution of anxiety $a(t)$ and sense of meaning $m(t)$ driven by changes in the level of physical comfort $f(t)$. Positive values of these two state variables indicate high anxiety and a "large" sense of meaning respectively. Anxiety has its everyday definition, and meaning describes a sense of purpose, direction, or understanding in life. Physical comfort alludes to access to food, shelter, medicine, health, etc. These variables have been chosen because intuitively, they are related in some way. A sense of meaning acts to decrease anxiety, but persistent anxiety may also decrease meaning. On top of these effects, one could argue that the anxious person interprets the world through a lens of anxiety, which creates more apparent stressors. This indicates that anxiety is self-perpetuating. As basic survival becomes a guarantee and people need to

of digital technology and polarization in time. The full argument states that the human response in time cannot be decomposed into separate parts from the respective histories of polarization and digital technology.

[4]The study of "complex systems" has its own body of literature within which complexity is given a technical definition. For example, a complex system is distinguished from a complicated one by not being decomposable into a sum of its parts. Here, I use the term in a more colloquial way to indicate a system which is very unpredictable.

find new and more abstract goals in life, physical comfort may reduce meaning. But, reliable access to basic comforts also acts to reduce anxiety.

You are completely free to, and probably justified in, contesting the relationships I am proposing. However, the goal of this informal model is to be *reasonable*, not rigorous. It is simply a candidate framework for this anxiety-meaning-comfort human system which is grounded in apparently plausible assumptions about how these variables are related. Whether this model is understood on the individual or societal level is not important–we are interested in getting a qualitative sense of the dynamics of this model. *In other words, we want to investigate how predictable the system's behavior is.*

As is common in physics and engineering, differential equations are the natural framework for modeling the time evolution of interrelated state variables. Because we model the interaction of the two quantities anxiety ($a(t)$) and meaning ($m(t)$), this will be a system of differential equations.[5] And finally, remember that for this system to even have a chance of reproducing intuitive features of the human system, it must be non-linear! One possible non-linear system which reflects the qualitative sketch of the relationships between these variables is the following:

$$\begin{cases} \frac{da}{dt} = a^3 - m^{\frac{3}{7}} - f^2(t) \\ \frac{dm}{dt} = -a^5 - f(t) \end{cases}$$

To solve for how anxiety and meaning evolve over time, we must specify a time history of comfort (force) for our toy human system and initial conditions $a(0)$ and $m(0)$. These initial conditions are interpreted as the baseline states of anxiety and meaning before we observe the effect of changing physical comfort perturbing the system. They are starting points. The time trajectory of comfort we will experiment with is a "saturating" exponential:

$$f(t) = c_0\big(1 - e^{-rt}\big)$$

This represents a fast initial increase of comfort which eventually levels off. The parameters $c_0$ and $r$ respectively determine the final value of comfort and the rate at which change takes place. Note that a generic non-linear system of differential equations will diverge to $\pm\infty$ unless carefully tuned. To avoid this, additional terms can be introduced to the system which discourage the state variables $a(t)$ and $m(t)$ from exceeding specified limits.[6] In some sense, this can be given a real world interpretation–in a well-functioning society, there are

[5] In this context, $G(\cdot)$ is conceptualized abstractly as the solution to the system of equations for a given force and set of initial conditions.

[6] To accomplish this, I add a penalty term to each time derivative of the form $-x^n \tanh(p(|x| - \ell)) + 1$ where $x$ is the state variable, $\ell$ is the specified limit, $n$ controls the strength of penalty, and $p$ is a positive number. As the limit $\ell$ is approached, this term becomes large and pushes the state variable back to zero. Plot this function to see how it works!

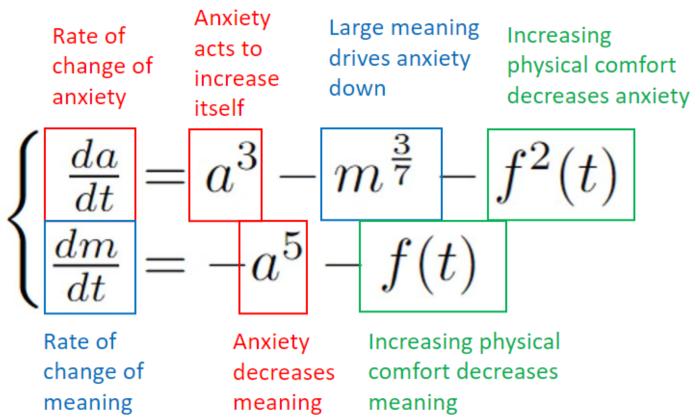



Figure 2: A non-linear system of differential equations representing the anxiety-meaning-comfort system. The restoring force terms are approximately zero unless the limits are approached, and are not shown here.

often restoring forces which tend to keep human systems from taking on extreme states. We will arbitrarily set the limits on the anxiety and meaning state variables at $\pm 1$ for simplicity. See Figure 2 for interpretation of the governing equations of the system.

We now have a candidate mathematical model of the system. It is non-linear in order to reproduce the richness of human responses. It is motivated by a qualitative understanding of how anxiety, meaning and physical comfort might interact, but cast in a somewhat arbitrary quantitative form. Furthermore, we have chosen the limits on the system states arbitrarily. The parameters $c_0$ and $r$ do not have clear physical meaning–what does an initial value of physical comfort $f(0) = 3$ (for example) correspond to in real life? Is the rate parameter $r$ shifting a time scale of hours, weeks, months, or years? These questions are not important for our purposes. We are less concerned with the precise quantitative predictions of the system. *What we want to investigate is how predictable its qualitative behavior is. Do anxiety and meaning oscillate? Does one go up and the other go down? Are these responses sensitive to initial conditions? Are they sensitive to magnitude and rate of the changes in physical comfort?* To answer these questions, we can solve the system over given time intervals for different initial conditions and parameters of the forcing function. MATLAB's built-in differential equation solver "ODE45" is used to solve the non-linear system. See Figures 3-6 for an exploration of some of the properties of the anxiety-meaning-comfort system.

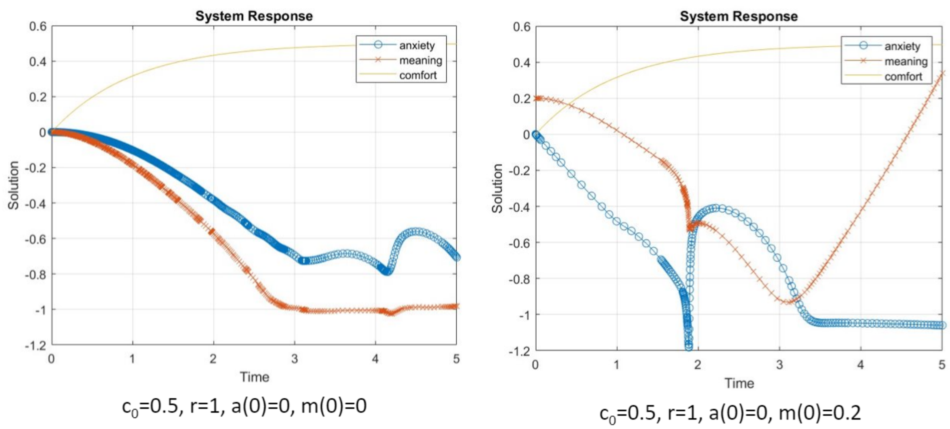



Figure 3: For a given force $f(t)$ small changes in initial conditions lead to different final states. On the left, anxiety and meaning start at the same level and both approach their lower bound. On the right, meaning starts at a slightly higher initial value, decreases at first, then approaches its upper bound. This demonstrates the final states of the system are sensitive to initial conditions.

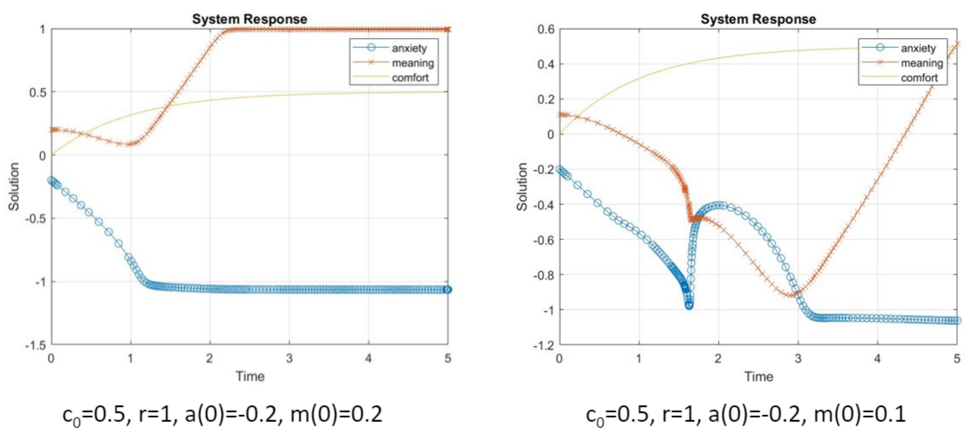
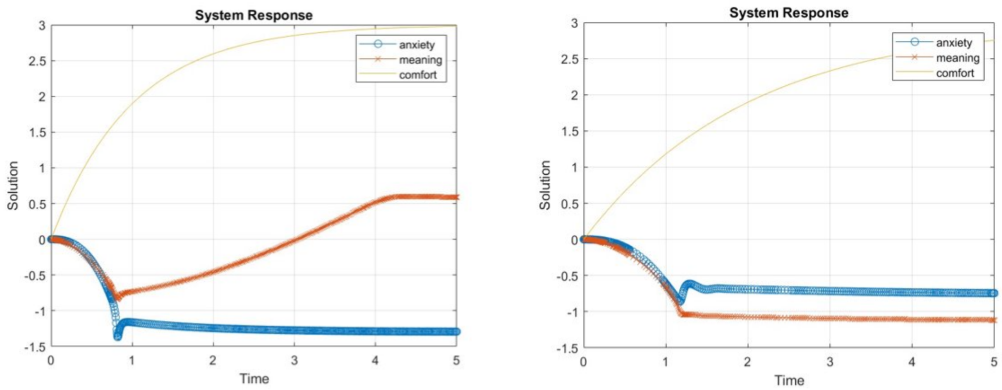



Figure 4: For given force $f(t)$, small changes in initial conditions can lead to the system approaching the same final state in very different ways. On the left, meaning approaches its upper bound and anxiety its lower bound. On the right, a small decrease in the starting value of meaning leads to a large initial decrease in meaning, which eventually is reversed. This is another indication of sensitivity to initial conditions.

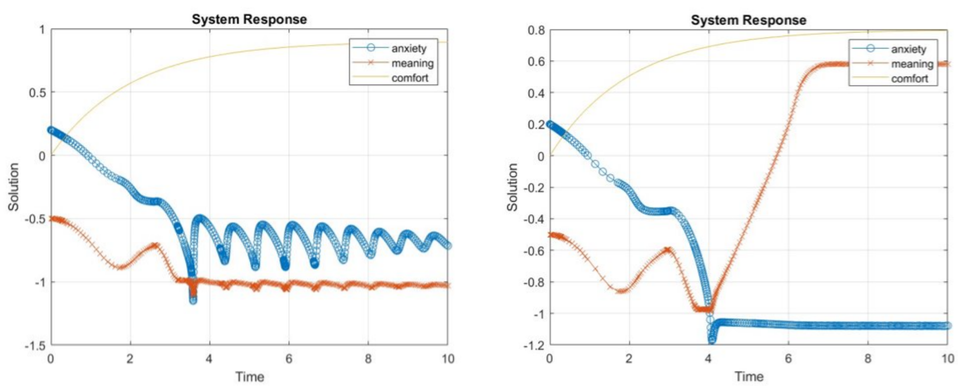
# Results

Figure 3 shows that the final state of the system is very sensitive to the initial conditions. Figure 4 shows that the manner in which the same final




$c_0$=3, r=1, a(0)=0, m(0)=0 $c_0$=3, r=0.5, a(0)=0, m(0)=0

Figure 5: For given initial conditions and final value of comfort, the system is sensitive to rate at which change takes place. On the left, comfort changes more quickly. Meaning approaches its upper bound whereas anxiety tends towards its lower bound. On the right, changes in comfort happen slowly and both variables approach their lower bound. This demonstrates that the final value of comfort does not determine the final state of the system.




$c_0$=0.9, r=0.5, a(0)=0.2, m(0)=-0.5 $c_0$=0.8, r=0.5, a(0)=0.2, m(0)=-0.5

Figure 6: For given initial conditions and rate of change of comfort, the system is sensitive to the final value of comfort. On the left, anxiety and meaning approach their lower bound with significant oscillations in anxiety. On the right, a small change in the final value of comfort has meaning attaining its upper bound and anxiety its lower bound. This demonstrates that the system response does not scale with the input force.

state is approached can also be very sensitive to the initial conditions. Figure 5 demonstrates that the character of the system response depends on how the final value of comfort is approached. Finally, Figure 6 shows that the nature of the system response also depends on what the final state of comfort is. Remembering that these features should apply to generic human systems, this should be troubling and counter-intuitive.[7] We do not expect that the dynamics of these systems depend chaotically on the minutia of environmental forces. We tend to assume that big effects must be the result of big causes. Yet, in the grand scheme of things, this is an extremely simple system: the two variables of anxiety and meaning are interrelated and change in time according to the state of physical comfort. We have made an attempt to capture these dynamics with differential equations, which we know must be non-linear to be realistic, and for which there are straightforward mathematical techniques to solve. It should be apparent that this model is a gross simplification and not to be taken too seriously. The point is not that this model tells us anything credible about the dynamics of anxiety and meaning in our lives. I hope you will agree that real human systems, depending on vast networks of interconnected "variables" and the vagaries of human will, are strictly more complex than our toy model here. *Yet, this toy model is already so complex as to defy intuition. Through extreme sensitivity to small changes in inputs and initial conditions, it exhibits chaotic behavior which makes even qualitative features of the response very difficult to predict.* And in general, increasing the complexity of a model will only serve to exaggerate its unpredictability.

## Conclusion

If you accept my argument about the scaling and interaction properties of any candidate model of human behavior, you will accept that models of human systems must be non-linear. And if you also accept that toy models in the form of systems of ordinary differential equations are strictly simpler than real human systems, *you have placed a serious restriction on how predictable you can expect human systems to be.* Even the simplest non-linear ODE's exhibit chaos to the point of being totally baffling. You may argue that this is a particular non-linear system, and that other non-linear models should not be this chaotic. I would encourage you to experiment with some others to test this hypothesis! The properties we have shown here should be expected of a generic non-linear model. Furthermore, you may argue that human systems cannot or should not be modeled mathematically, a point which deserves serious consideration. But here, I claim not that math is a good model for human behavior, but that in their inherent non-linearity, high-dimensional structure,[8] and aversion

[7] The idea of the "butterfly effect," which states that a butterfly flapping its wings in one continent could cause a hurricane in another, comes from these properties of non-linear systems. This is another example of a troubling consequence of non-linearity.

[8] This just means that there are many interrelated variables needed to describe the state of the system.

to formalization, human systems are strictly more complex (and therefore less predictable) than these toy mathematical systems. And these simple systems already exceed the abilities of our intuitive reasoning! Given that effective personal and political decision making requires informal models of how the world responds to potential interventions, this is rather a troubling conclusion. If human systems are so complex as to resist mathematical formulation, and even simple mathematical systems surpass the capabilities of intuition, how can we have any faith in the decisions we make in the world? Can we have confidence that our visions for change and progress are beneficial if we cannot understand or predict how the world responds to such changes? We often encounter claims of apparent certainty about *what should be done* in social and political contexts. Implicitly, this a claim that given causes will produce a particular set of effects. The purpose of the admittedly clunky anxiety-meaning-comfort system was not to solve a particular problem, but to raise the general question: *is it ever fair claim certainty about cause-and-effect where human systems are concerned?*

Though mathematics may never be the *lingua franca* of personal and political decision making, it can give us insight into why these problems remain hard even after hundreds of years of scientific and technological advancement. If nothing else, this thought experiment should be humbling–next time you find yourself saying *if X then Y* without a well-defined mathematical model in hand, consider that you may be claiming to have intuition about a high-dimensional, non-linear system. In some situations, the tools to solve problems of this sort exist. Predictive models are powerful tools for simple and low-stakes experimentation with cause-and-effect relations. They tell us something about how possible actions map onto possible outcomes. This is the domain of computational science–from aerodynamics to drug discovery, high-dimensional non-linear systems are mined daily in industry and academia to much avail. But rarely do these explicit mathematical models exist for human systems. In the absence of these quantitative models, we rely on tools such as intuition to make sense of the world. But, as we have seen, intuition is not a trustworthy guide in making precise predictions about non-linear phenomena. This is a deliberately disturbing conclusion–I interpret this to mean that in spite of all our technological and scientific sophistication, we operate essentially in the dark with regards to many important social and political questions. We simply do not know what the consequences of taking certain actions in the world will be.

How are decisions made about complex problems then? I would argue values are one answer to this apparent bind. Values are first-principle commitments which are to some extent outcome-independent. An act can be viewed as *inherently* right or wrong, thus ignoring uncertain downstream effects. Values such as freedom, justice, equality, compassion, etc. can be used as filters to constrain action and make some sense of what should be done. As I see it, it is an act of faith to believe that adherence to values leads straightforwardly to desirable personal and social outcomes. Yet I think we do this unconsciously: we do not demand exact predictive models as prerequisites to making decisions, rather we subject possible actions to the test of values. People successfully take action and the world is not entirely unpredictable, at least most of the time. There must be some hidden epistemic trick at work, wrangling the chaos of life's various non-linearities. So I think the bottom line is this: when a system is too complex to model mathematically or make sense of intuitively, there may be no alternative but to lean more heavily on values as guides to shepherd decision making. And in realizing that we make decisions constantly despite the unreliability of our mental models, I think there is benefit in reflecting more seriously on what values drive these decision making processes.