Model-Based Thinking

Idea In Short

No model captures reality, and every useful one leaves things out. Model-based thinking makes that trade on purpose. A model is a simplified construct, such as an equation, a diagram, or a simulation, that stands in for a real system so you can ask what happens if something changes. Scott Page, a scholar of complex systems, argues that leaders make better decisions when they apply many models and not one. Epidemiologists use compartment models to track spread, and managers can borrow the same logic for adoption, queues, and growth. This article explains what models do, how to build and test one, why several beat one, and how to avoid being fooled by a clean simulation.

A product team wants to know whether a referral program will make the user base explode. One analyst builds a spreadsheet: each user invites three friends and one in five signs up. The model shows rapid growth. Another analyst notes that invitations fade as the pool of nearby friends shrinks. The second model shows growth that levels off. Neither is complete, and together they reveal what the team needs to measure.

What a model is

A model is a simplified representation of a real system. It can be an equation, a diagram, a table, or a computer simulation. What matters is that it captures a few relationships clearly enough that you can ask questions of it.

Scott Page, a University of Michigan professor of complex systems, political science, and economics, built a course and a book around the idea. Wikipedia notes that he is linked to the online Model Thinking course and that he published The Model Thinker with Basic Books in 2018.1

In an interview with Knowledge at Wharton, Page points to the SIR model from epidemiology, which divides a population into susceptible, infected, and recovered groups.

He observes that once you learn such a model, you can apply it anywhere that something spreads like a virus.2

That portability is a major benefit. A model of spread built for disease can describe the adoption of a product, the diffusion of a rumor, or the spread of a fault through a network.

Why simplification helps

Models are wrong because they simplify. An extract from The Model Thinker states that models omit details, and that by considering many models we can overcome the narrowing that comes with rigor.3

Omission is the point. A map that showed every tree and pebble would be useless for finding the road. A good model leaves out what does not matter for the question and keeps what does.

The skill lies in choosing what to keep. For a pricing question, a model of demand and cost may be enough. For a question about team culture, you need a model of incentives and relationships. The wrong model gives a precise answer to the wrong question.

Why many models beat one

Page's central argument is that leaders should apply several models to each problem. The extract describes the many-model approach as building on the old idea that we achieve wisdom through a multiplicity of lenses, an idea it traces back to Aristotle.

A summary of the book on a reading platform puts the logic simply: any single model will likely fail, and each model provides a piece of the puzzle that together creates a more complete understanding.4

In the Wharton interview, Page makes the same case and notes that investor Charlie Munger has long advocated a lattice of models. A data science writer echoes the point, arguing that an ensemble of models is good for humans and for machines.5

The practical rule is to use at least three models on any important question. If they agree, confidence rises. If they disagree, the disagreement shows where uncertainty lives.

Building a simple model

Begin with the question. "How many support agents will we need next year?" is a modeling question. "How is the business doing?" is not.

List the key quantities and how they relate. For the support question, these might be customer count, tickets per customer, handling time, and agent hours. Draw arrows between them.

Write the relationships in plain numbers. For example, tickets equal customers times tickets per customer. Staffing equals tickets times handling time divided by productive hours. Then run the model with your best estimates, and with ranges to see how sensitive the answer is.

Testing and improving a model

A model earns trust through testing. Feed it past data and see whether it reproduces what happened. If a model of last year's tickets misses by half, do not rely on it for next year.

Look at where it fails. Failures reveal missing pieces, such as seasonality or a product launch. Add the most important missing piece, and test again.

Keep models small. Each addition makes them harder to understand and check. A model that you cannot explain to a colleague in five minutes is hard to trust.

Models for spread, flow, and feedback

Several families of models appear again and again in business. Spread models, like SIR, describe adoption and contagion. Flow models track queues, inventory, and cash. Feedback models capture reinforcing and balancing loops, such as growth that feeds on itself until it hits a limit.

Page mentions that a Markov model, in which the future state depends on the present one, can also describe many processes, such as customers moving between plans or loyalty states.

Learning a handful of these patterns pays off. When you meet a new problem, you can ask

which pattern it resembles and borrow the structure. The habit turns each new situation into a variation on something you know.

Using models in teams

Models make assumptions visible. When a team builds a diagram of how a decision works, members discover that they hold different pictures. The discussion moves from opinions about outcomes to disagreements about specific links, which are easier to resolve.

Use models to explore scenarios. Change an input and watch what happens. Ask what would have to be true for the plan to fail, and test those conditions.

Share models openly, along with their limits. A one-page note stating the purpose, the key assumptions, and the known gaps lets others use the model well and challenge it.

Choosing the right level of detail

Detail is a cost as well as a benefit. A very simple model is easy to understand and check, but it may miss a driver that matters. A very detailed model captures more, but it needs more data, takes longer to build, and hides its logic.

A useful rule is to start with the simplest model that could answer the question, and add detail only where the answer is sensitive to it. Run the model, change an input by a third, and see if the conclusion shifts. If it does, that input deserves more care. If it does not, leave it alone.

Match the model to the decision. A choice that you can reverse next month needs a rough model. A commitment that locks in millions deserves several models, checked against data, and reviewed by someone who did not build them.

A hypothetical example

Imagine a hypothetical subscription company that wants to cut churn. The finance team builds a simple model in which each month a fixed share of customers leaves, and it predicts steady decline. The customer team builds a second model that distinguishes new customers, who leave quickly, from long-term ones, who rarely leave. The two disagree

about the benefit of retention work.

A third model, a flow of customers through onboarding stages, shows that most losses happen in the first two weeks. The company concentrates on onboarding and sees churn fall. The case is invented, but it shows how several models can expose what one hides.

Cautions

Do not confuse the model with the world. A neat simulation can create false confidence, especially when its output looks precise.

Avoid fitting a model to the past so closely that it fails on new data. A model that explains everything that has happened may predict little.

Finally, state your assumptions. If you cannot say what the model leaves out, you cannot judge when to distrust it.

- 1Scott E. Page
- 2Scott Page on the model thinker
- 3Many-model paradigm
- 4The Model Thinker, summary
- 5Five types of thinking for a high performing data scientist

Summary

Model-based thinking means using simplified constructs to explore how a real system might behave. Models help you spell out assumptions, test changes cheaply, and see consequences that intuition misses. Every model is wrong because it simplifies, so the discipline lies in choosing models that fit the question, checking them against evidence, and using several to cover each other's blind spots. Leaders who master it ask what a model includes, what it leaves out, and how the answer would change if the omissions mattered. Take one decision you face, sketch a simple model of it on one page, and list the three assumptions that would change your answer most.