34th Annual INCOSE international symposium

hybrid event

Dublin, Ireland
July 2 - 6, 2024

Panel 288

Model-Based Systems Thinking (MBST)

Panel Members

Meet our panel at INCOSE IS 2024:

Empowering real world complex problem solving: Socio-technical Applications of Model-Based Systems Thinking (MBST)

Wednesday, 3 July, 18:00-20:10 IST

Kamran Shahroudi
Moderator

Systems Fellow @ Woodward, Inc. & Professor of SE @ Colorado State University

Golam Bokhtier
Presenter/Panelist

Systems Engineer at Northrop Grumman & PhD Candidate at Colorado State University

Quentin Saulter
Panelist

Senior Program Manager at Office of Naval Research & PhD Candidate at Colorado State University

Sarwat Chappell
Panelist

Senior Program Manager at Office of Naval Research & PhD Candidate at Colorado State University

Kirk Reinholtz
Panelist

Retired Principal Engineer at NASA JPL & PhD Candidate at Colorado State University

Model-Based Systems Thinking (MBST) refers to using rigorous modeling frameworks, languages and tools that help us understand and potentially influence complex emergent behavior of socio-technical systems. MBST enforces systems principles and identifies leverage points within the structure and mental models driving the behavior of complex systems in order to increase predictability, controllability, reliability, profitability, and other significant figure of merits of our solutions and policies.

Key Questions for the Panel

1. What are the rigorous frameworks, languages and tools for MBST?
2. What are some examples of real-world applications of MBST ?
3. Is System Dynamics almost synonymous with MBST ?
4. Is MBSE rigorously enabling Systems Thinking?
5. Shall MBST be discipline agnostic or specific ?
6. Why is the adoption of System Dynamics so low in mature industries?

Each panelist to attempt at least one question before Q&A with the audience!

Panel Discussion

- 00 – 10: Introduction of the topic and panelists (Team) – Two slides with topics and introductions of the panel.
- 10 – 20: Overview of rigorous modeling methods for systems thinking with examples (Kamran)
- 20 – 30: MBST Framework applied to Wildfire UAV (Golam)
- 30 – 40: MBST Framework applied to Innovation (Quentin)
- 40 – 50: MBST Framework applied to Physical Training (Sarwat)
- 50 – 60: Practical Hurdles and Potential Future of MBST (Kirk)
- 60 – 120: Wrap up and Q&A from the audience

Section 1: Overview of rigorous modeling methods for systems thinking

Kamran Eftekhari-Shahroudi

Systems Fellow @ Woodward, Inc.
Professor of SE @ Colorado State University.

Model-Based Systems Thinking

1. Model-Based Systems Thinking (MBST): *Rigorous* application of *Systems Principles* to solve *Real-World* problems.

2. *Rigor* comes from *Discipline Agnostic* modeling *Methods* (Frameworks, Languages, Tools).

3. MBST rigorously updates the *Mental Models with* high leverage *Influence* strategies to improve emergent complex behavior of systems.

4. High leverage means higher predictability, controllability, reliability, profitability, and other significant measures of our solutions and policies.

5. Strategies are changes to *Purpose*, *Structure* and *Patterns of Behavior*

What are the Rigorous Modeling Methods for Systems Thinking?

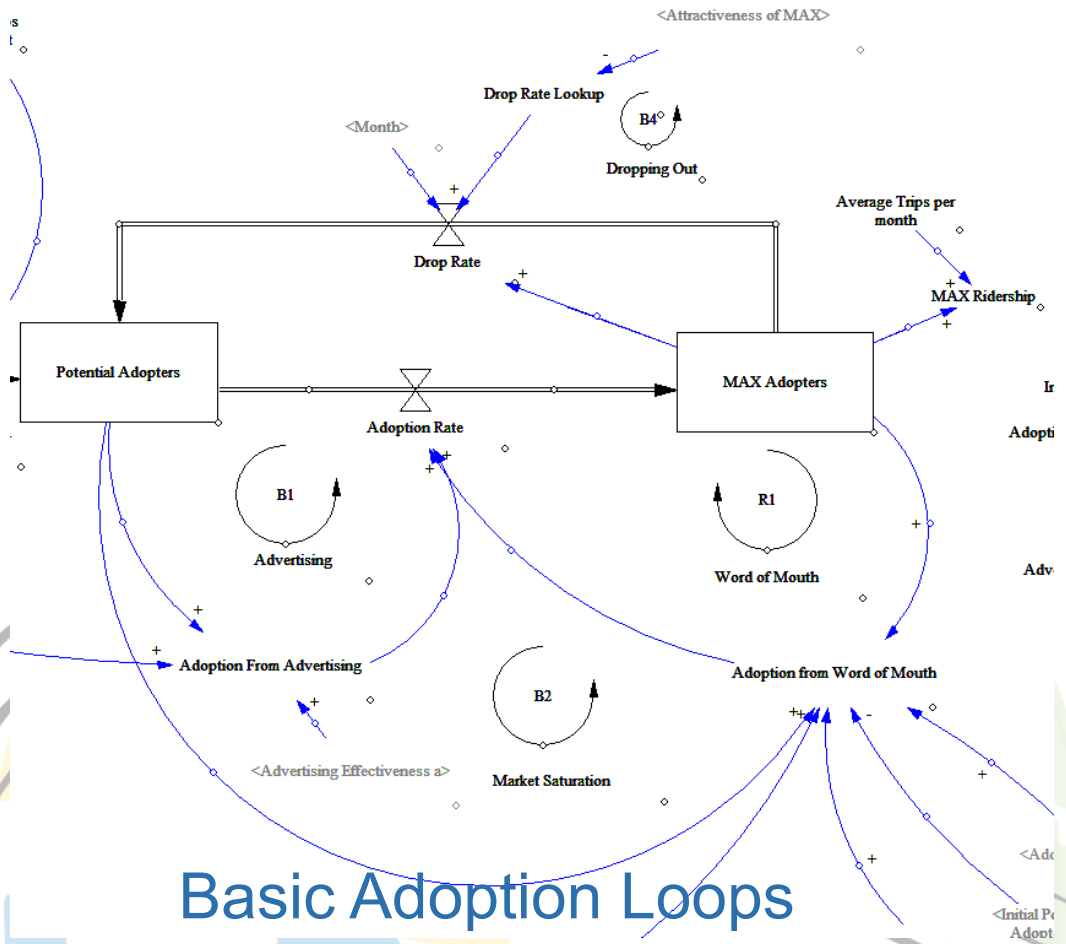
- System Dynamics (Forrester, Meadows, Sterman, Senge etc.)
  - Most mature but least penetration
- DSM/N2 (Architectural Visualization/Optimization)
  - Simplest but low penetration
- Architectural Modeling (SysML, MBSAP)
  - Niche penetration into S/W, H/W and Systems Engineering
- Stochastic / Agent-Based Modeling
- AI/Machine Learning
- Symbolic Math
- Causal Inference/Graph Analysis

There is a potential for cross fertilization of these methods!

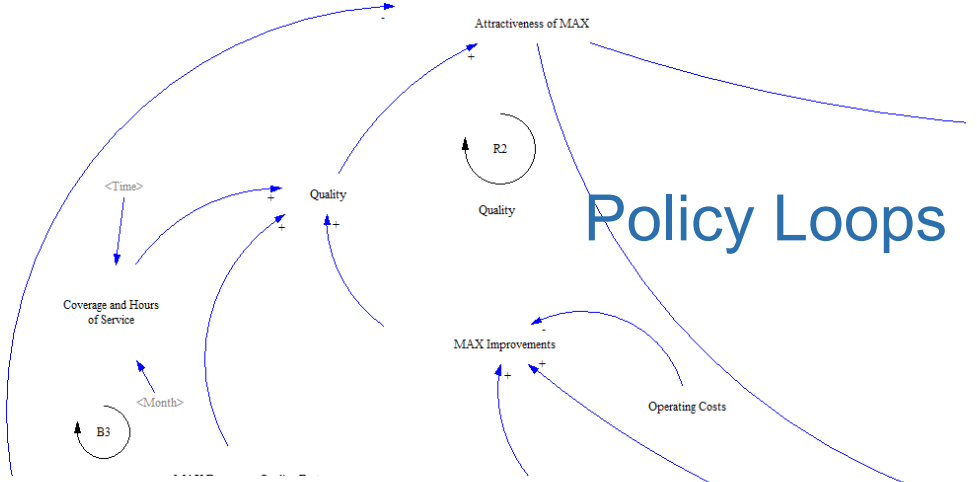
Real-World Application of MBST: MAX Transport in Fort Collins

- Started service May 2014
- 3 students in contact with City planners built an SD model of Ridership in Dec 2014
  - explain the rapid rise, fall and plateauing of ridership after introduction experienced in Minneapolis earlier
- Model helped:
  - Understand the Complexity of Ridership Growth
  - Understand the Complexity of Attractiveness
  - Understand Impact on Car Transportation and vice versa
  - Understand the Robustness of MAX planning
    - Advertising, Word of Mouth, Quality, Capacity Planning, New East-West line opening
    - Where to invest $'s to escape the ridership plateau
  - Ridership grew to 450000 in April 2019!

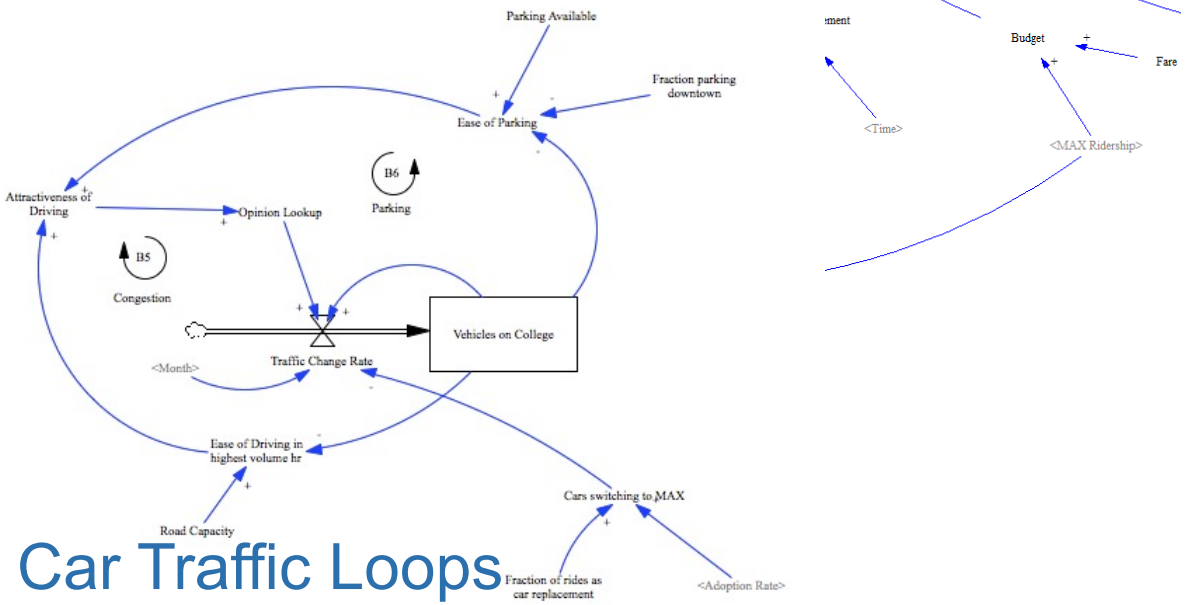
Max Transport SD Model



Basic Adoption Loops



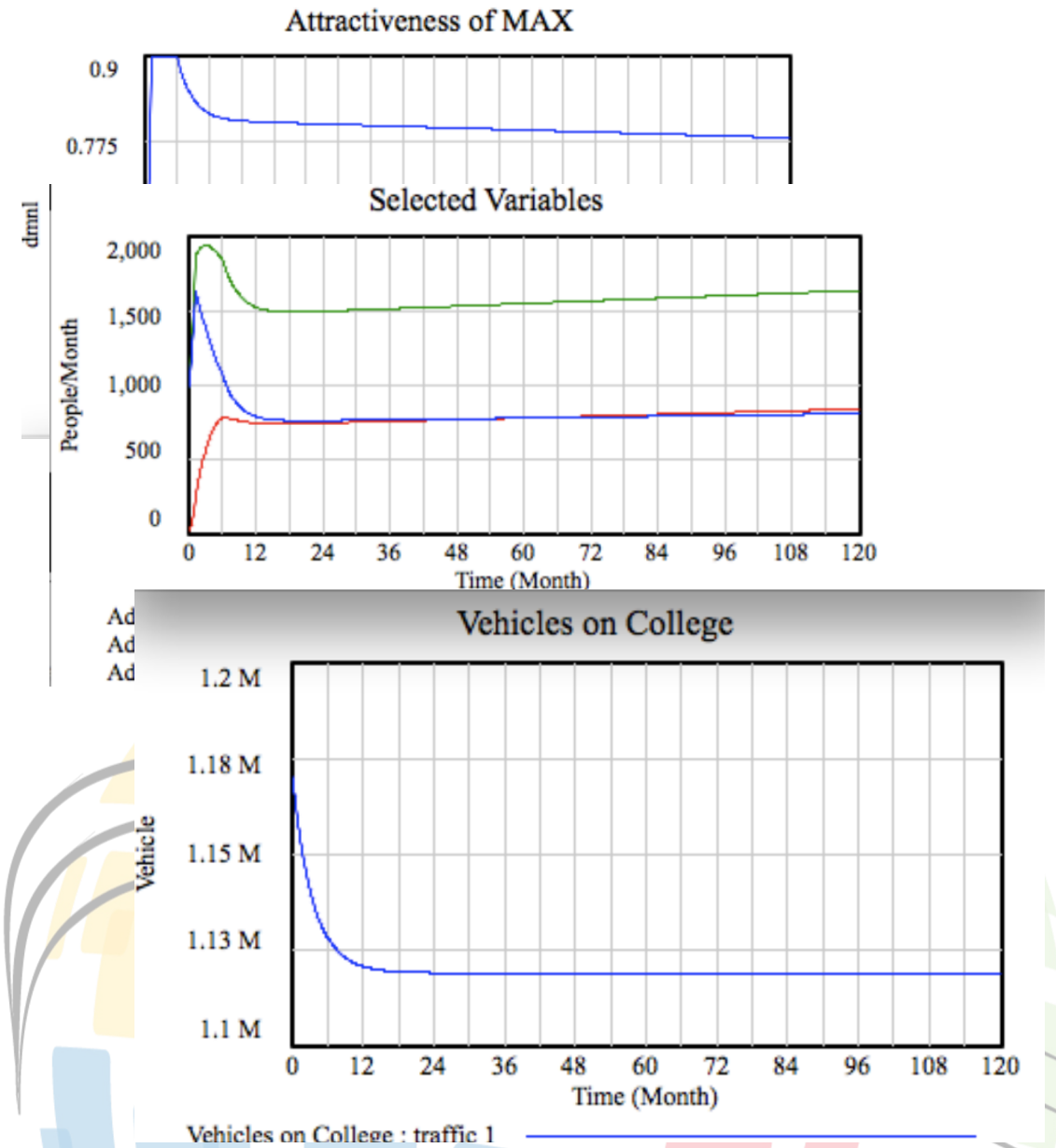
Policy Loops

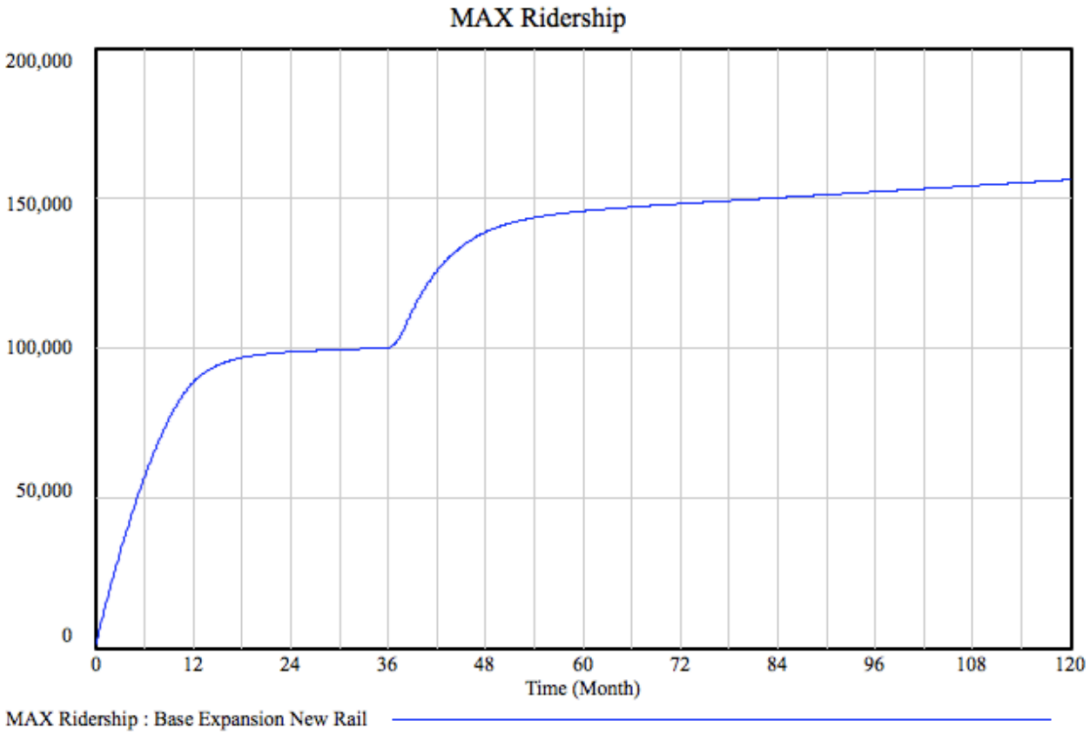


Car Traffic Loops

Model & Results by Barbara Frye, Jesse Parker, Bing Chen & Kamran

Max Results

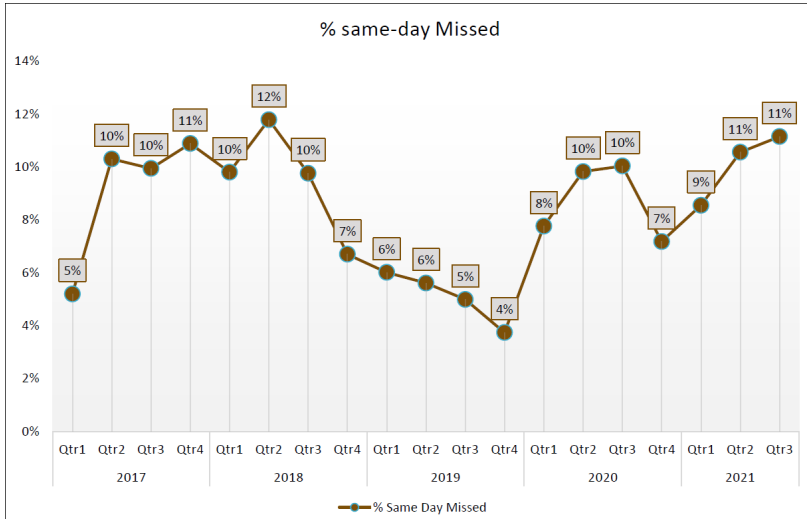




Predicting the Impact of Doubling Capacity to Boost MAX Ridership

Real-World Application of MBST: Patient No-Show for Same Day Missed(SDM) Appointments

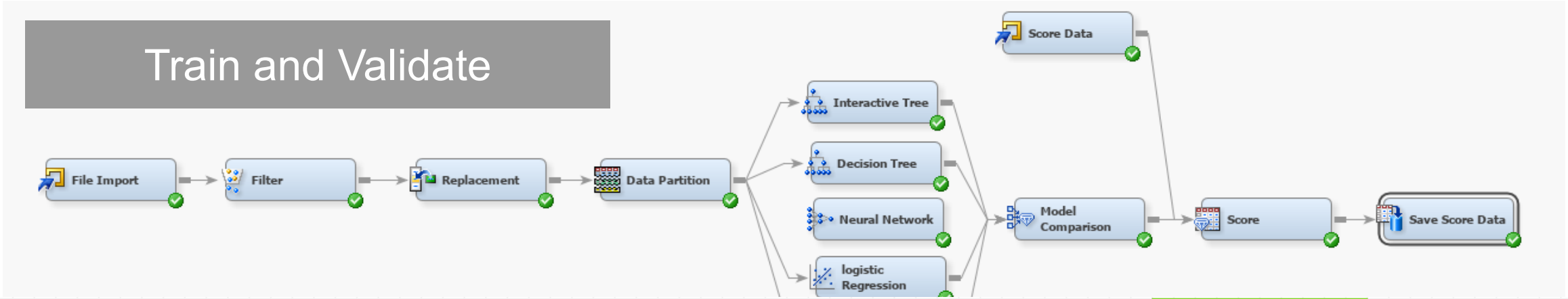
- Imaging center in CA had double digit losses!
- Researcher built a Predictive Model:
  - To estimate a probability of no-show for each caller based on SeenYN, Appt Date, Exam Desc, Age, Referring Phys, Suite, Site, Sex etc.
  - To conclude “why” a patient may become a SMD
- Re-Architected the patient scheduling system to integrate the Predictive Model using MBSAP
- Implemented a proactive call confirming strategy to enable targeted interventions
  - For example, if the model predicted the patients would be claustrophobic then the staff could discuss specific options for helping to complete the exam



Year	Total Revenue	Lost Revenue Due to Same-day Missed Appointments	% Lost of Total Possible Revenue
2017	$19M	$1.5M	7.3%
2018	$21M	$1.8M	7.9%
2019	$22.5M	$1.2M	5.1%
2020	$15.5M	$1.3M	7.7%

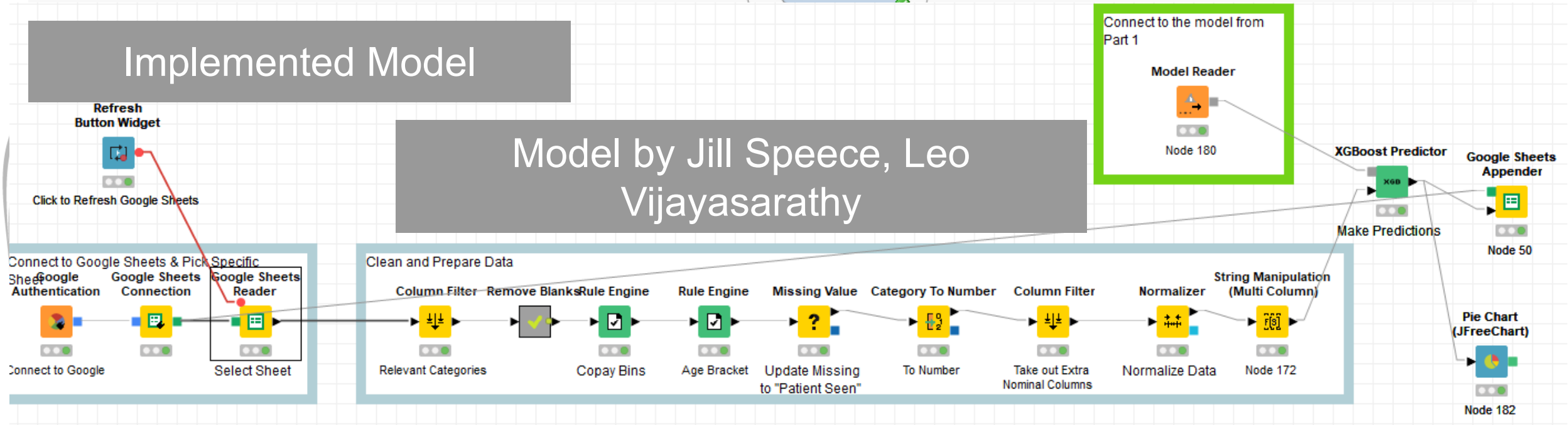
Predictive Model: Development & Usage

Train and Validate



Implemented Model

Model by Jill Speece, Leo Vijayasarathy



Measured Results at the Clinic

# of Days Experiment Conducted Properly	# of Patients Call Confirmed	# of Patients Who Should Have Been Call Confirmed	# of Patient Who Did Not Need Call Confirm
17	360	1170	4683
Average % Seen Rate	88%	82%	85%

Daily Average # of Patients for Call Confirm	90
# of Patients Who Show With Call Confirming	78.75
# of Patients Who Show Without Call Confirmation	73.35
Difference	5.40
Average Reimbursement for Mix of Exams Call Confirmed	$193
Daily Revenue	$1,043
Potential Annual Revenue	$262,869

Modality	CT	DX	FL	MG	MR	US
Total # of Exams	154	9	16	60	165	601
Average Reimbursement	$247	$56	$141	$225	$374	$130
Total Reimbursement	$38,038	$504	$2,256	$13,500	$61,710	$78,130
Weighted Average Reimbursement	$193.17					

Financial Impact

Annualized Savings
~$260k

Does not consider cost of staff member

Double digit improvement in clinic losses !

Is System Dynamics Synonymous with MBST ?

- No! or It depends on how SD is utilized!
  - SD is much more mature since Sterman text published 2000
  - SD is very capable with broadest range of real-world applications: particularly socio-technical
  - SD is very difficult to master and not intuitive or natural to most people requiring major training.
- We recognize SD, DSM/N2, Architecting (SysML, MBSE), AI/ML, Graph Analysis as other modelling methods for MBST
- MBST Framework should build on and expand beyond just SD for more effective adoption!

Is MBSE rigorously enabling Systems Thinking?

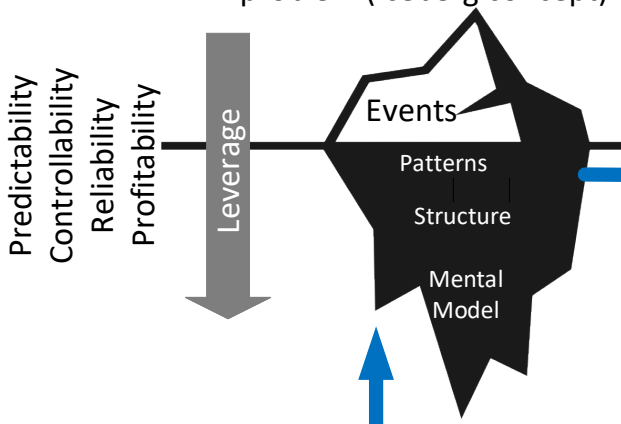
- SE is NOT = ST
- SE is process and machinery.
- ST is the philosophy and way of approaching (complex) problems.
- Successful SE's need (some level of) ST for sure.
- Successful ST's may have never heard of SE/MBSE!.
- Betting 2:1 against MBSE unless:
  - SP's and SW's are dominant!

MBST Framework & Application to Wildfire Detection

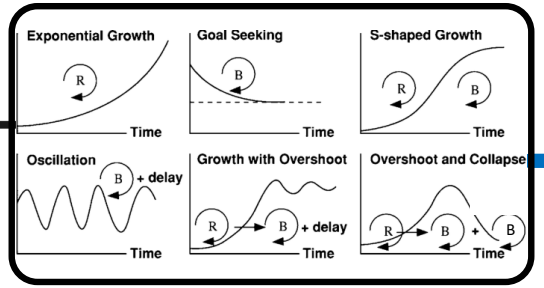
Golam Bokhtier

Generic MBST Framework

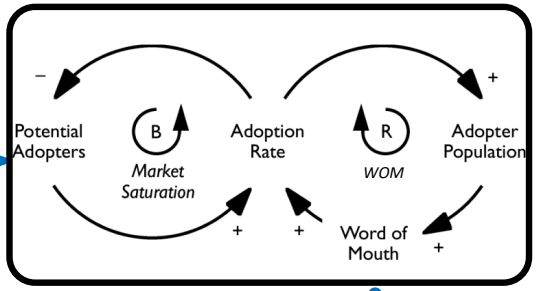
1- Start here – define the problem (Iceberg concept)



2 – Identify relevant patterns of behavior (Ref-modes)

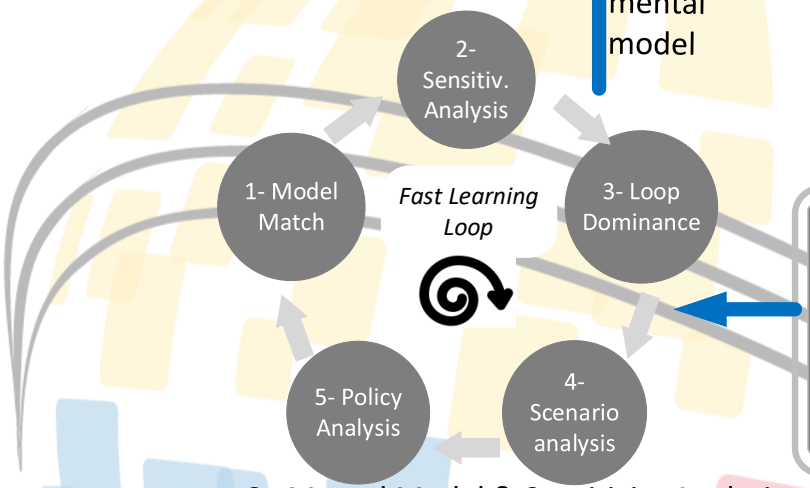


3 - Develop Causal Relations (Causal Loops)

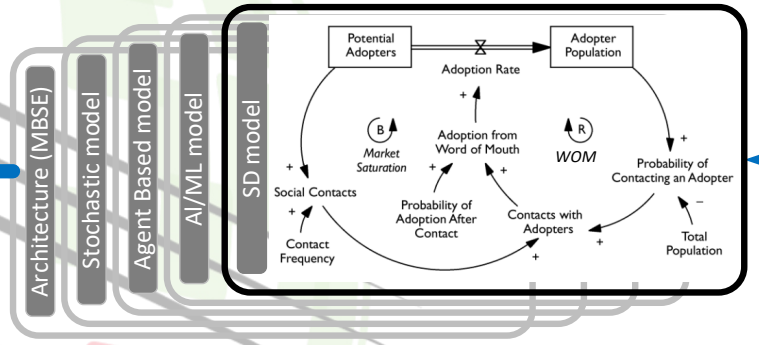


Update mental model

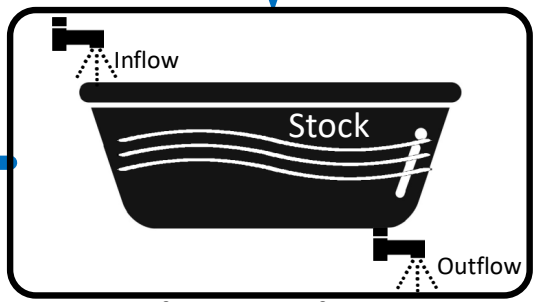
Slow Learning Loop



6- Mental Model & Sensitivity Analysis



5- Create Structure & Behavior Model

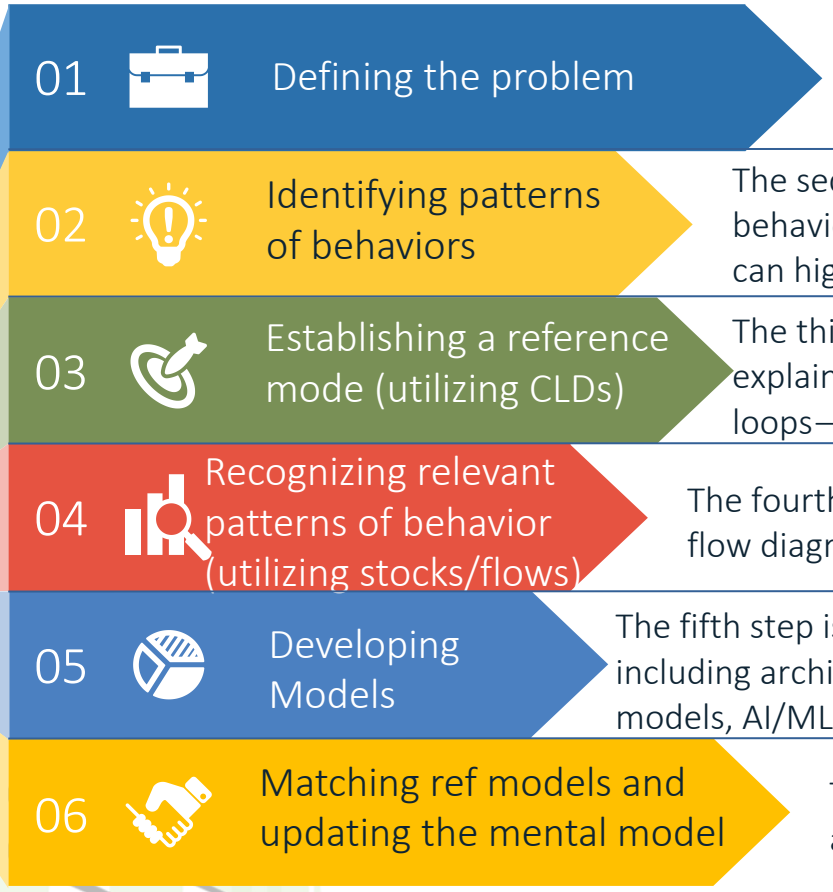


4- Classify Nature of Variables in Causal Relations (Stocks, Flows, Units)

Generic MBST Framework (Slow learning loop)

MBST Framework

Generic MBST Framework provide flexibility beyond using SD models



The first step, depicted on the top left, is the iceberg concept, where the mental model is the root of the system.

The second step involves identifying relevant patterns of behavior. Reference modes and data from actual events can highlight different patterns

The third step is constructing causal loop diagrams to explain the interactions between different types of loops—balancing and reinforcing.

The fourth step involves creating stock and flow diagrams.

The fifth step is modeling. Various types of models can be used, including architecture models, stochastic models, agent-based models, AI/ML models, and system dynamics models.

The sixth step is mental model and sensitivity analysis using reference modes.

Generic MBST Framework (Fast learning loop)

2 Sensitivity Analysis

he second step, part of the fast learning loop, is to perform sensitivity analysis. This helps us understand the system's behavior under different conditions.

3 Loop Dominance

The third step is to identify loop dominance, determining which feedback loops are more influential in the system.

1 Model Match

The first step is to match the model with the reference model. This gives a good understanding of how sensitivity works in the currently implemented model.

5 Policy Analysis

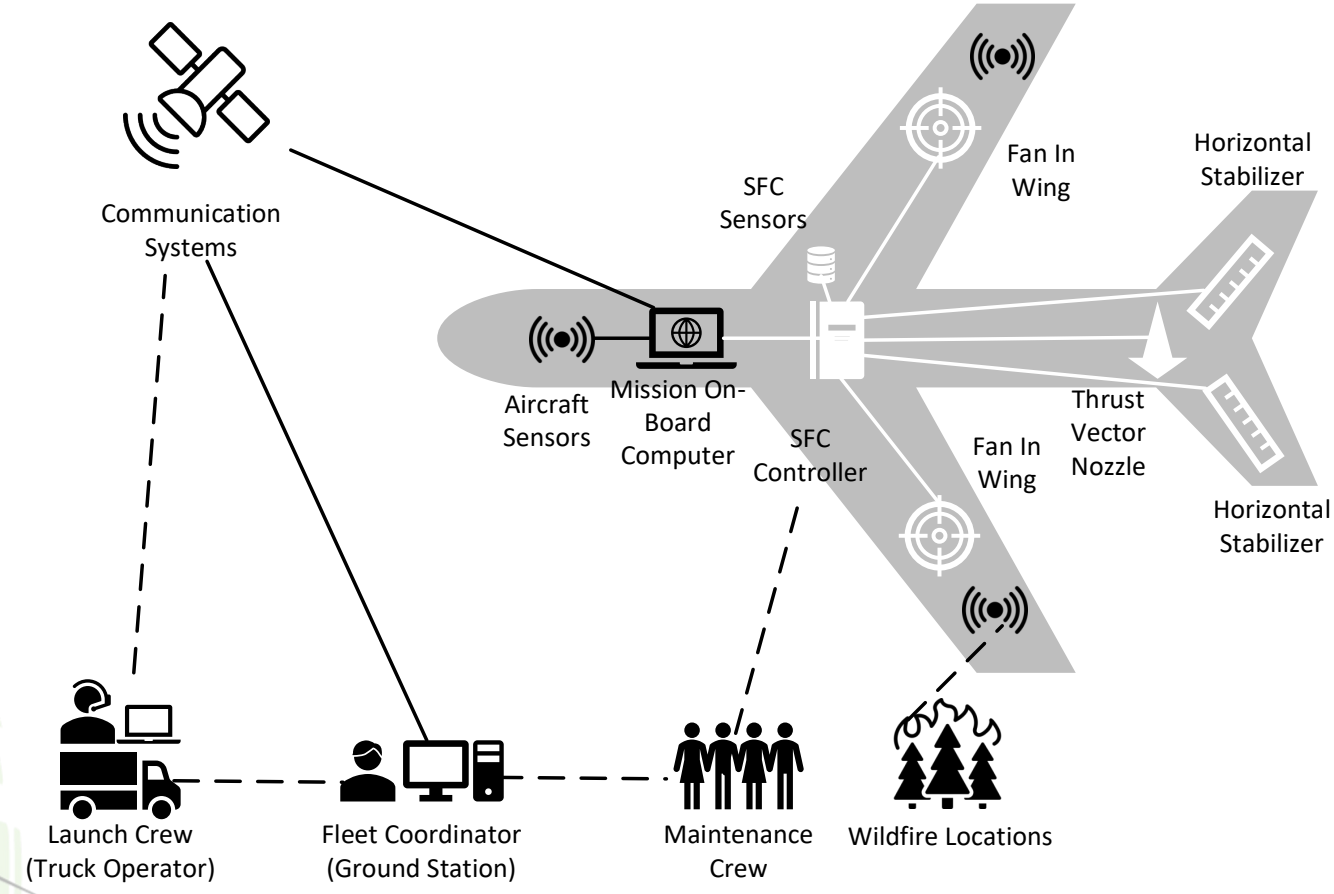
The fifth step is policy analysis. Here, we predict the intended and unintended behaviors of different policies or controls.

4 Scenario Analysis

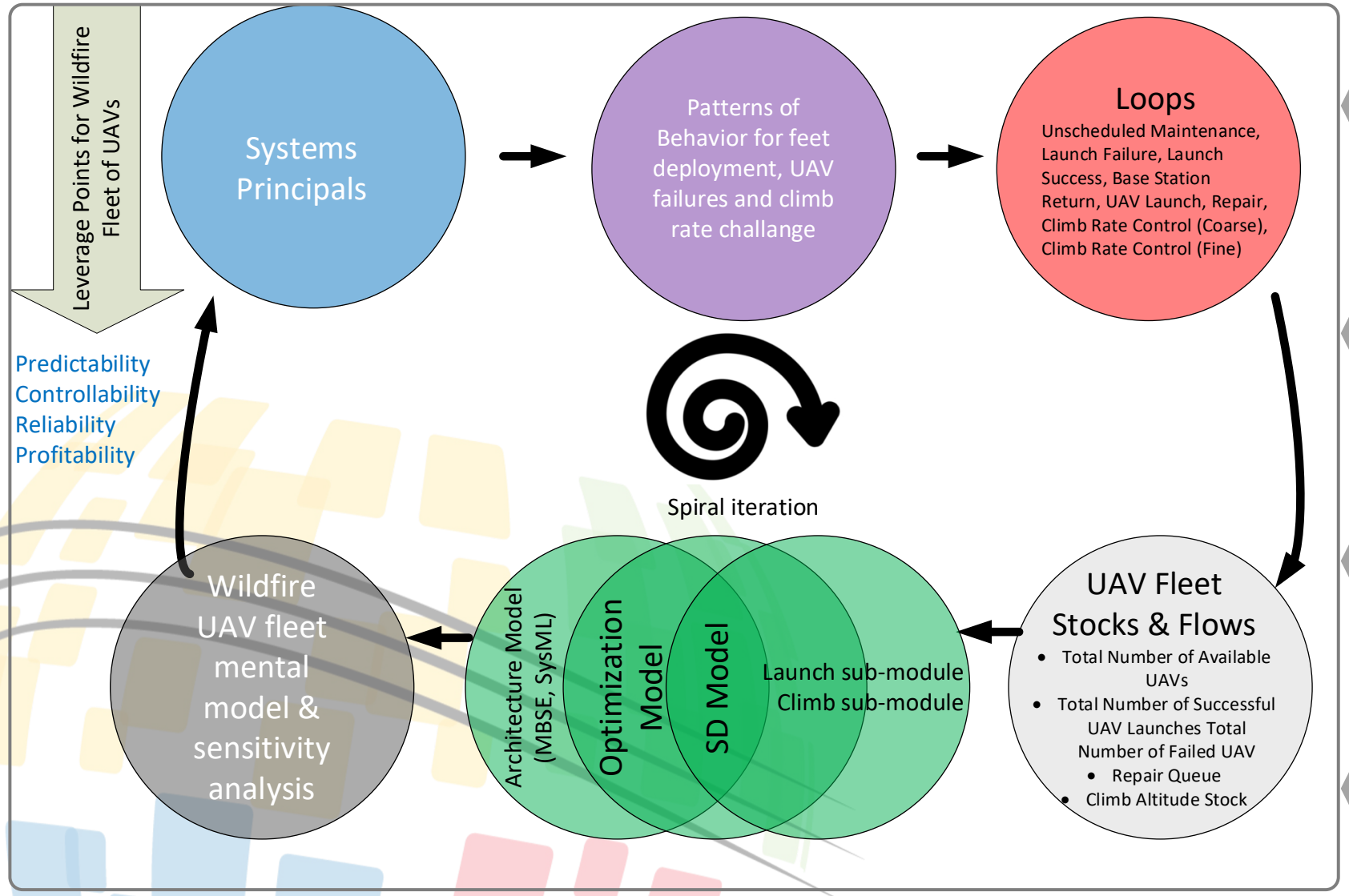
The fourth step involves scenario analysis, where we test different scenarios to see their effects on the system.

MBST Framework applying Wildfire UAV Fleet Deployment

1. **Holistic Understanding of wildfire detection and communication:** Provides a comprehensive view of how various components and stakeholders interact within the system.
2. **Scenario Planning:** Allows for the simulation of different scenarios to predict outcomes and prepare for various contingencies for UAV fleet deployment issues.
3. **Identification of Leverage Points:** Helps identify critical points where small changes can have a significant impact on the system's performance due to deployment and/or UAV design.
4. **Optimization:** Aids in developing optimized deployment strategies for UAVs to maximize efficiency and effectiveness in optimization of deployment or waypoints or design.
5. **Risk Management:** Enhances the ability to foresee potential issues and mitigate risks through better planning and analysis. Optimization problem to understand and address risks.
6. **Stakeholder Communication due to impacts of wildfire:** Improves communication with stakeholders by providing clear visualizations and models of the system's dynamics.



MBST Framework applying Wildfire UAV Fleet Deployment



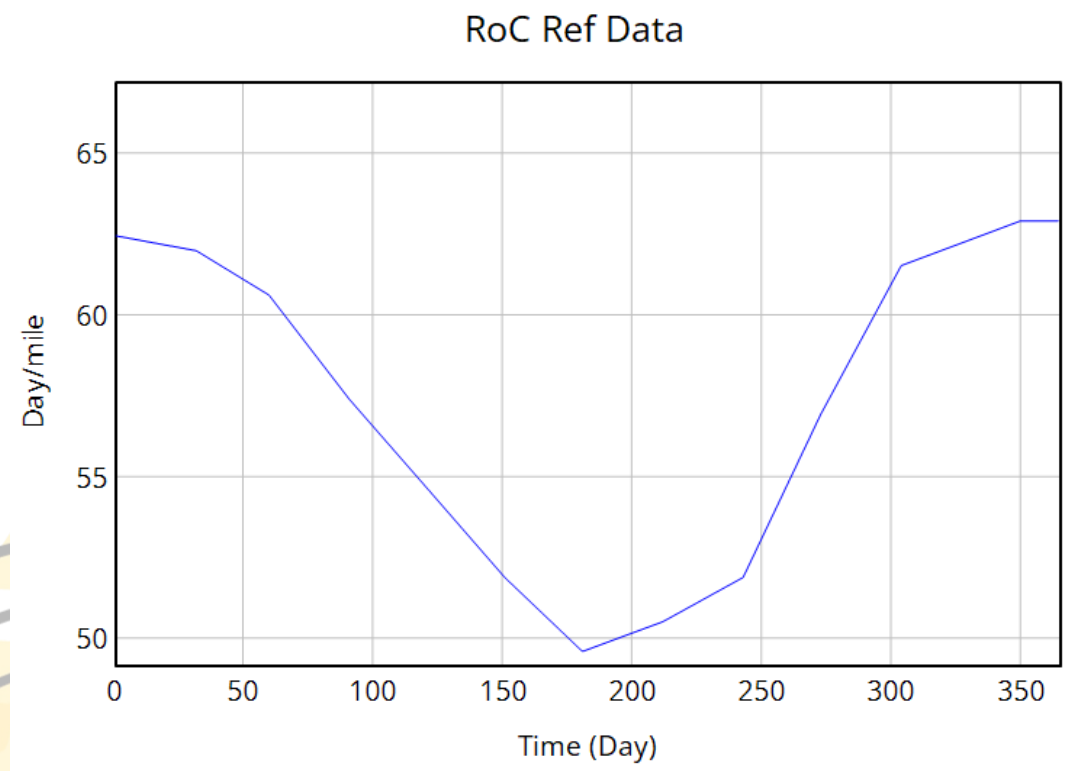
SD Modeling Process
(Process to develop Wildfire UAV Fleet Deployment)

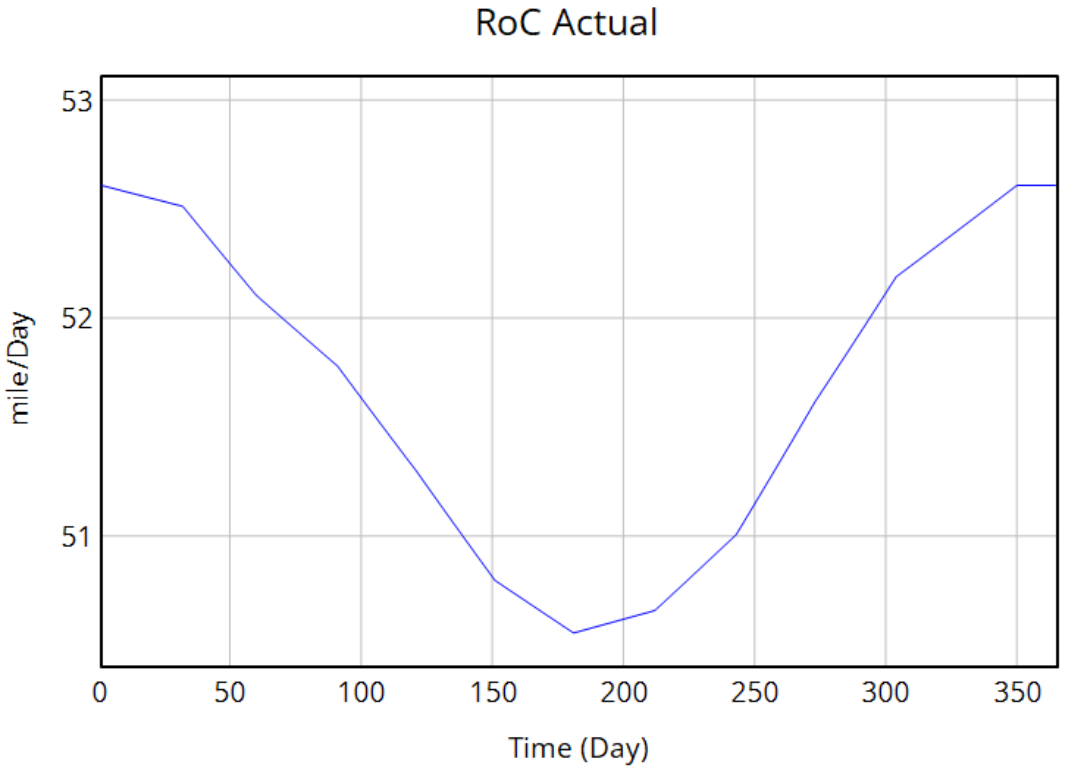
Architecture Modeling Process
(UAV Flight Controls and UAV Design)

Optimization Modeling Process
(UAV Fleet deployment objective functions)

Incremental Validation against Test Cases

Reference Mode - Comparison of actual Rate of Climb (RoC)/Climb Rate in model





Is MBSE rigorously enabling Systems Thinking?

MBSE (alone) Works but not efficient

Quick Initial Development
Implementation Challenges
Systems Thinking Importance
Potential Risks
Missed Opportunities

MBSE (alone) Architecture Model

Serves as Architecture Model
Systems Thinking
Effective Structuring
Integration Challenge
Holistic Approach Needed

MBST Framework and MBSE

Higher Assurance
Focus Areas
Comprehensive Understanding
Enhanced Decision-Making
System Optimization.

MBSE can implement a model but not guaranteeing that Systems Thinking principles are implemented.

Systems Thinking and Causal Inference

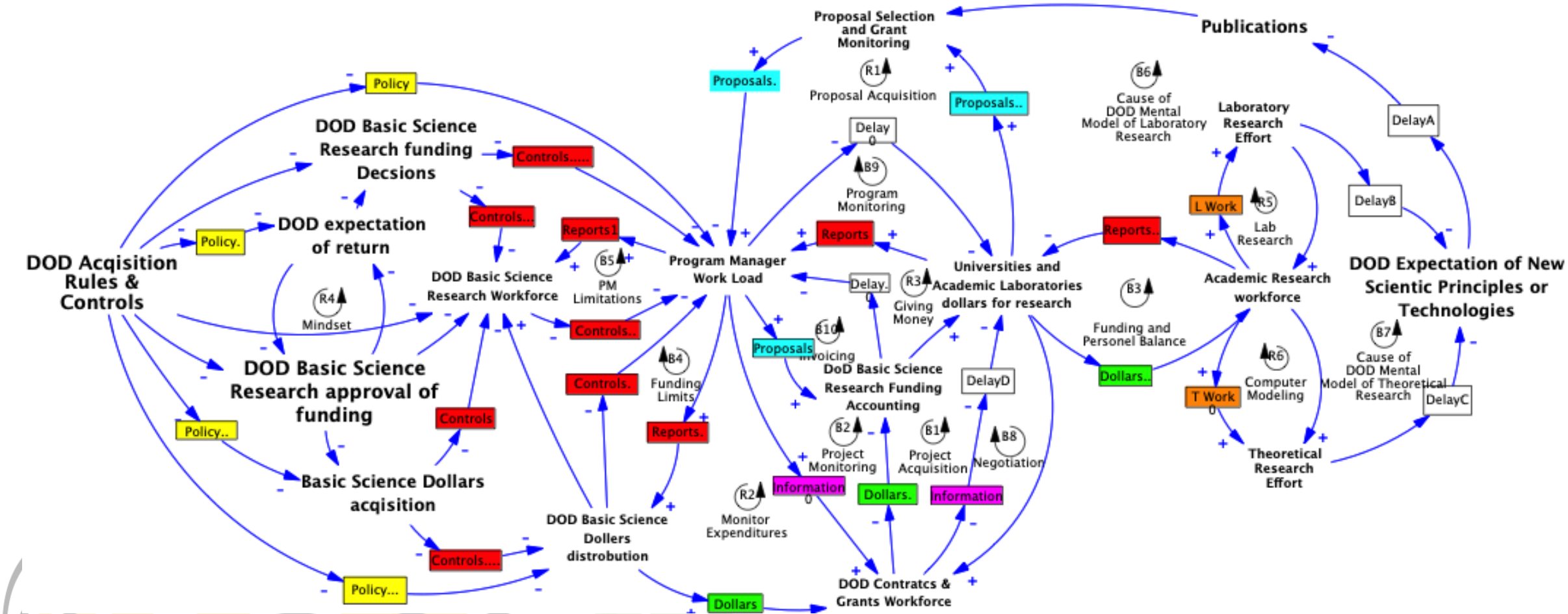
Quentin Saulter

Senior Program Manager at Office of Naval Research
PhD Candidate at Colorado State University

Understanding Complexity of Innovation

Both systems thinking and causal inference are used to understand complex systems.

Systems thinking involves considering multiple variables and their interactions within a system, while causal inference aims to identify the possible mechanisms that might have generated historic observations.


Proposal Selection and Grant Monitoring
Publications
Proposals.
R1
Proposal Acquisition
Proposals..
B6
Cause of DOD Mental Model of Laboratory Research
Laboratory Research Effort
DelayA
Policy
DOD Basic Science Research funding Decsions
Controls.....
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B9
Program Monitoring
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Delay8
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Reports1
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DOD Acqisition Rules & Controls
DOD Basic Science Research Workforce
B5
PM Limitations
Program Manager Work Load
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R3
Giving Money
Universities and Academic Laboratories dollars for research
Academic Research workforce
DOD Expectation of New Scientic Principles or Technologies
R4
Mindset
Controls..
B10
Invoicing
Proposals
B3
Funding and Personel Balance
B7
Cause of DOD Mental Model of Theoretical Research
DOD Basic Science Research approval of funding
B4
Funding Limits
Controls.
DoD Basic Science Research Funding Accounting
DelayD
Dollars..
R6
Computer Modeling
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DelayC
Policy..
Controls
Reports.
B2
Project Monitoring
B1
Project Acquisition
B8
Negotiation
Basic Science Dollars acqisition
R2
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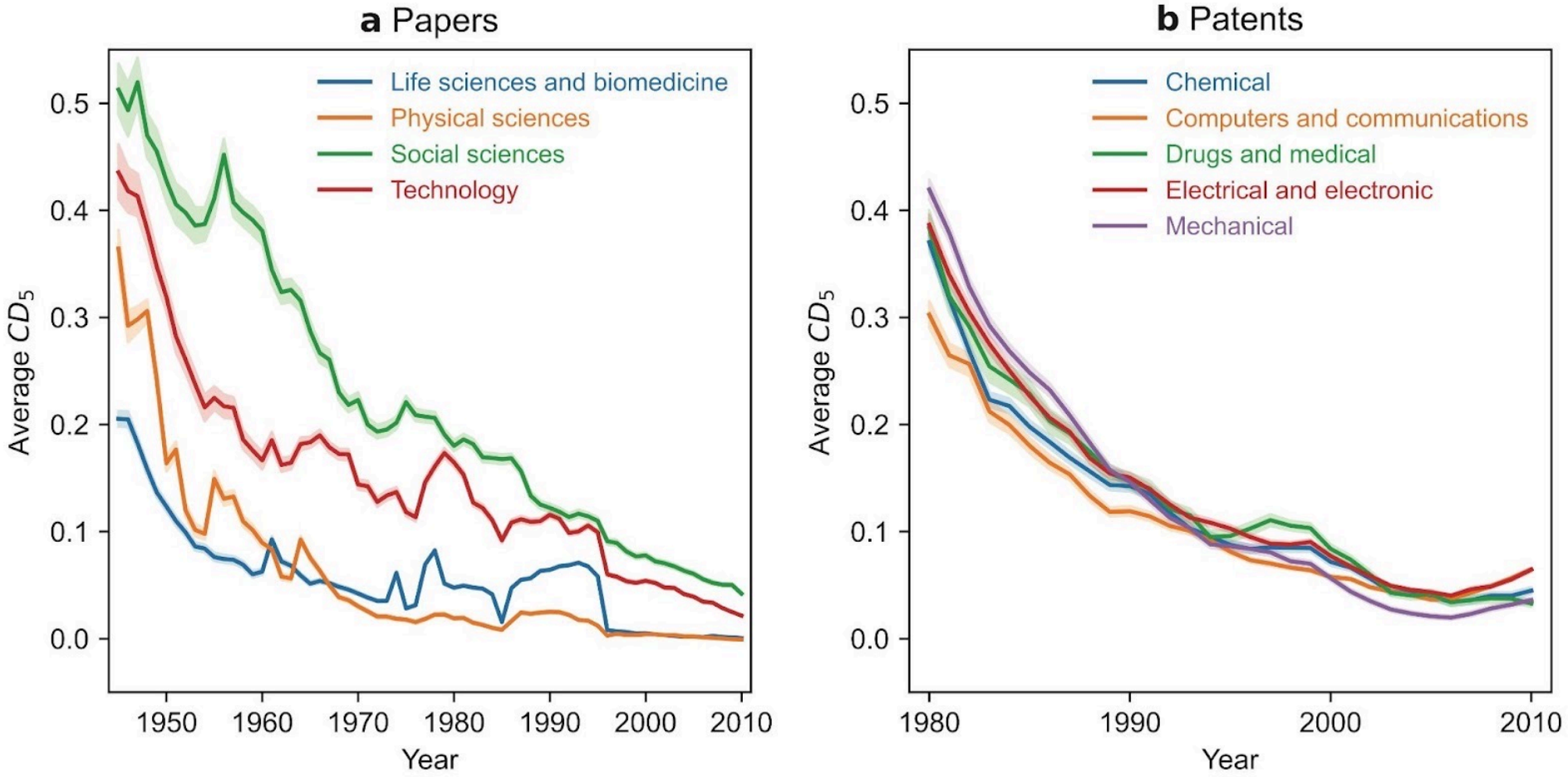
Information
Theoretical Research Effort
Controls....
DOD Basic Science Dollers distrobution
Policy...
Dollars
DOD Contratcs & Grants Workforce

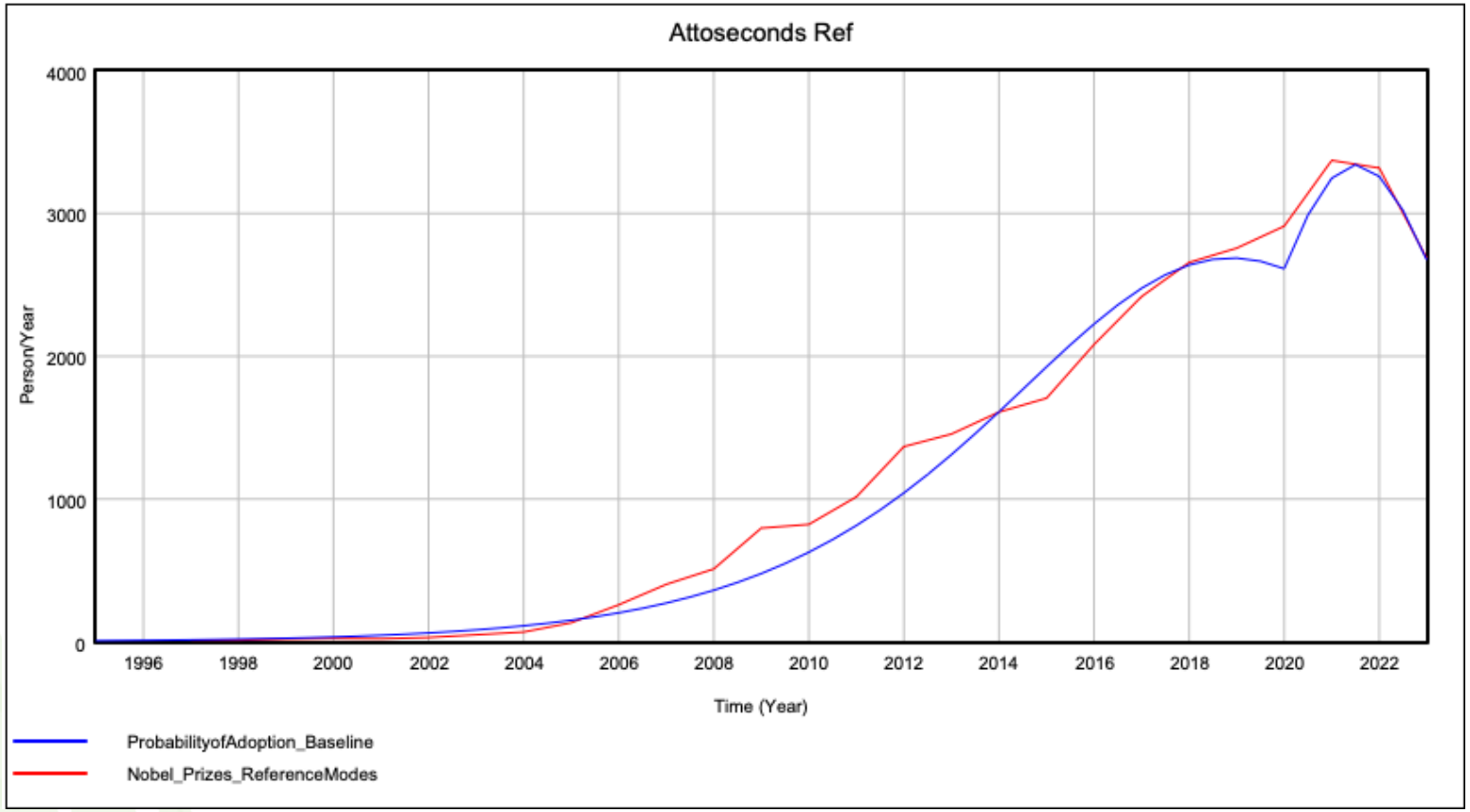
Science and technology are becoming less disruptive



Causal Relationships

- Systems thinking emphasizes the relationships among system parts.
- Causal inference is inherently linked to Systems Thinking, as causes let us better predict the future and intervene to change it by showing which elements of a system have the capacity to affect others.

Dynamic Model Based Innovation Metric Simulation Matching Reference mode

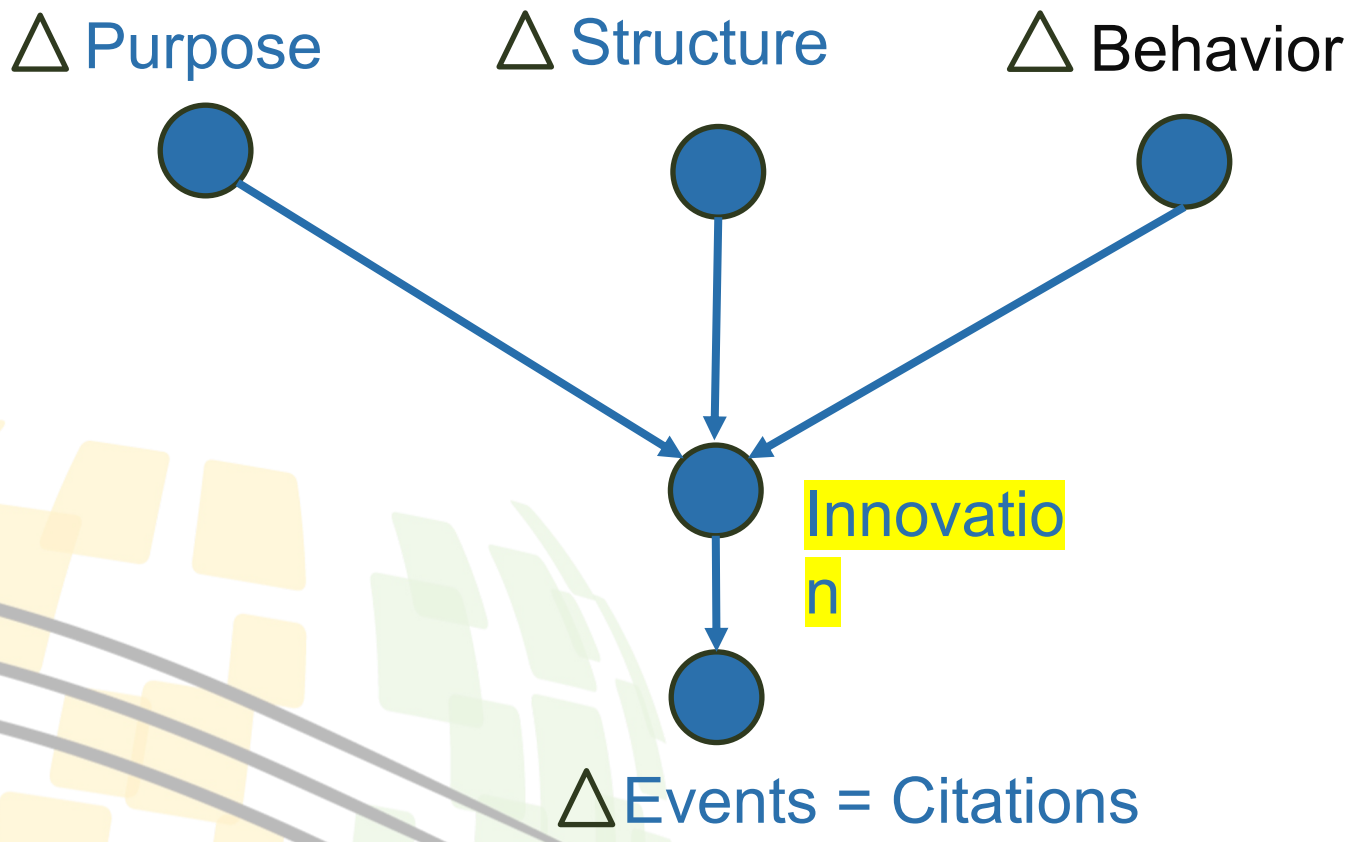


This graph is the Dynamic Model reference fit of Citations of Nobel Prize in Attoseconds Physics to validate to correct predictions of the dynamic model. Settings for the model are Conditional Probability 50% of being Cited with no changes in Purpose, Structure, or Behavior. This shows the model can reproduce actual outcomes.

Modeling and Simulation

- Systems thinking enables causal inference in the development and interpretation of models and simulations.
- For example, causal inference can determine the values of variable used in simulation models and interpret the observed phenomena.

Axiom 5: Innovation Causal Diagram Directed Acyclic Graph

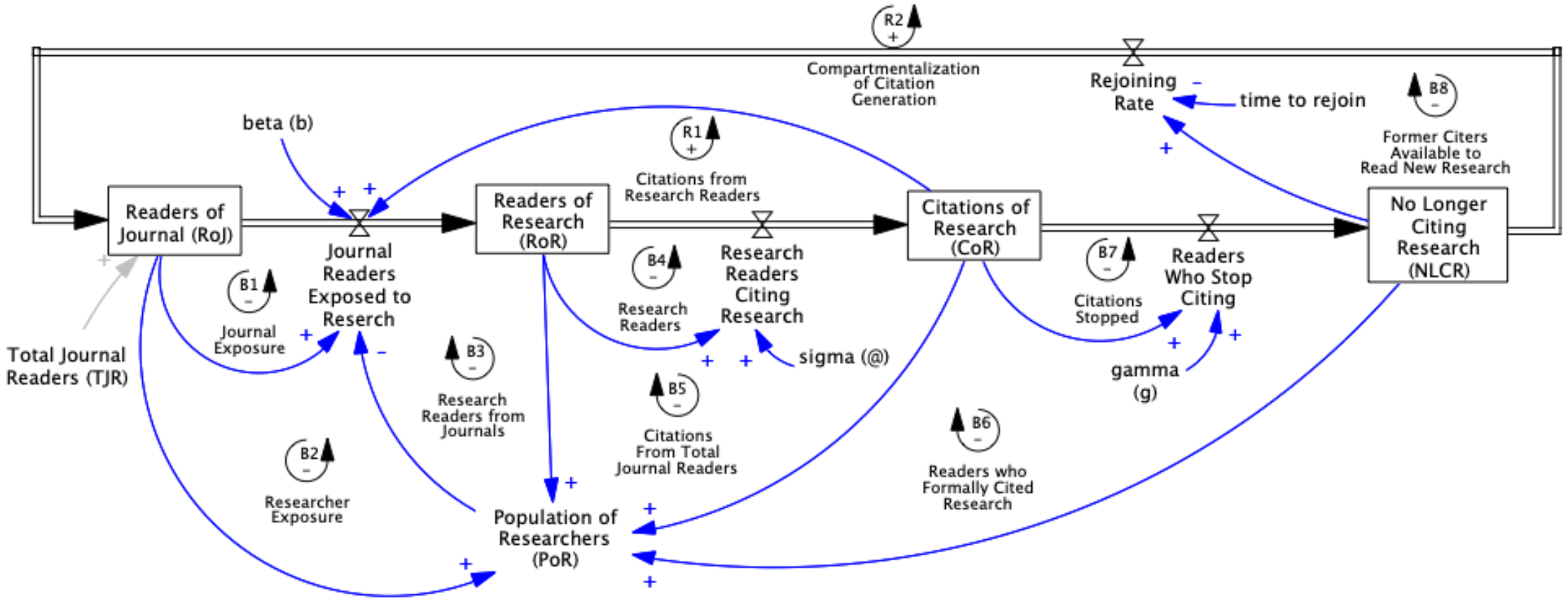


Change Sparks Innovation

Dynamic Interrelationships

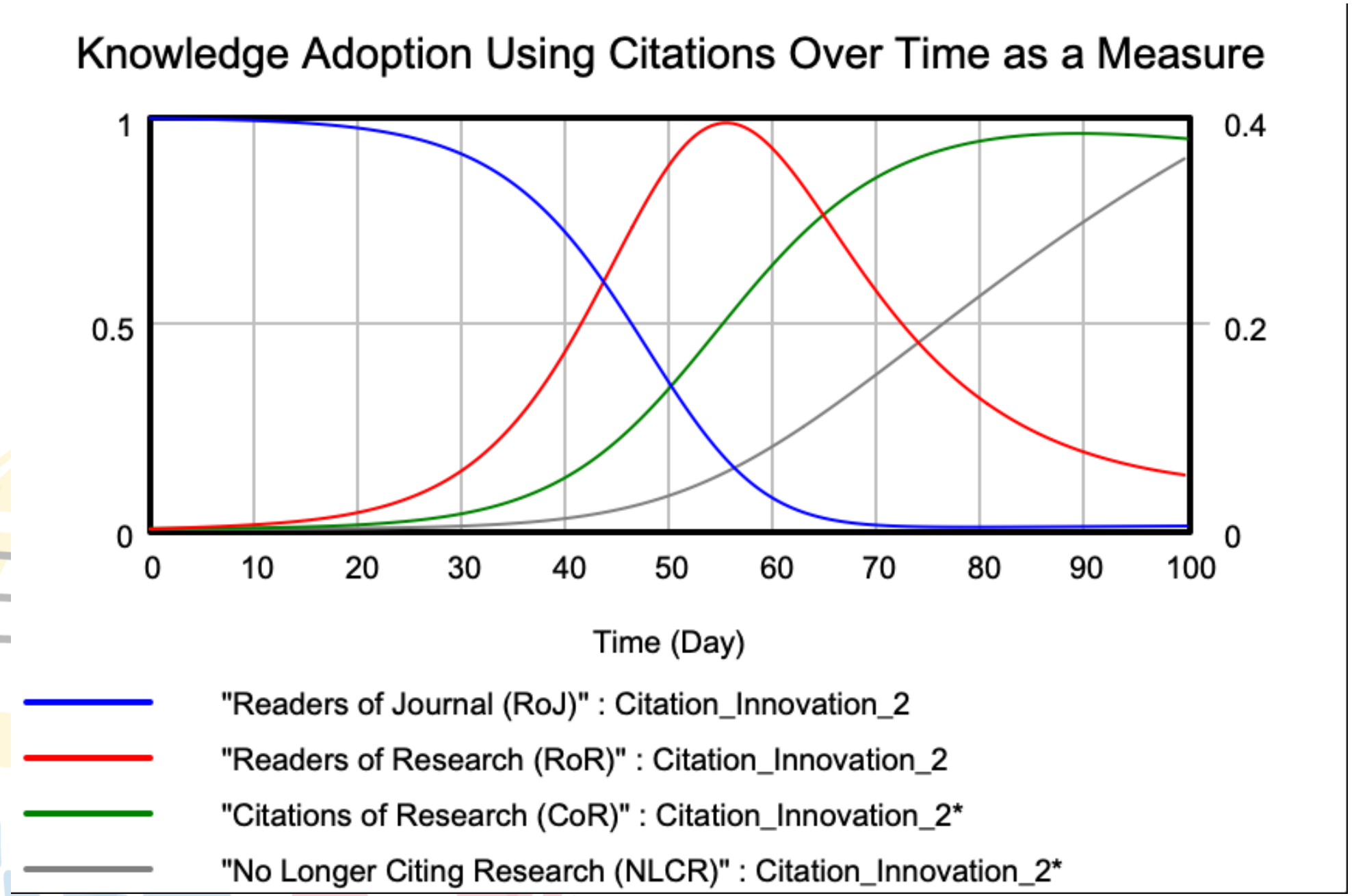
- Systems thinking provides a visual representation of dynamic interrelationships through the use of cyclic causal diagrams.
- Causal inference, enables the identification of independent and actual effects of specific components within complex systems.

Systemic Understanding of Innovation



Addressing Complex Issues

- Both systems thinking and causal inference can be used to address complex issues.
- For example, the adoption of complex systems dynamic models enables us to predict the amount of spread of a disease, causal inference allows us to find the where the disease came from.


Knowledge Adoption Using Citations Over Time as a Measure
1
0.5
0
0.4
0.2
0
0
10
20
30
40
50
60
70
80
90
100
Time (Day)
"Readers of Journal (RoJ)" : Citation_Innovation_2
"Readers of Research (RoR)" : Citation_Innovation_2
"Citations of Research (CoR)" : Citation_Innovation_2*
"No Longer Citing Research (NLCR)" : Citation_Innovation_2*

Shall MBST be Discipline Agnostic or specific ?

Physiological Application - Enhancing Fitness with MBST

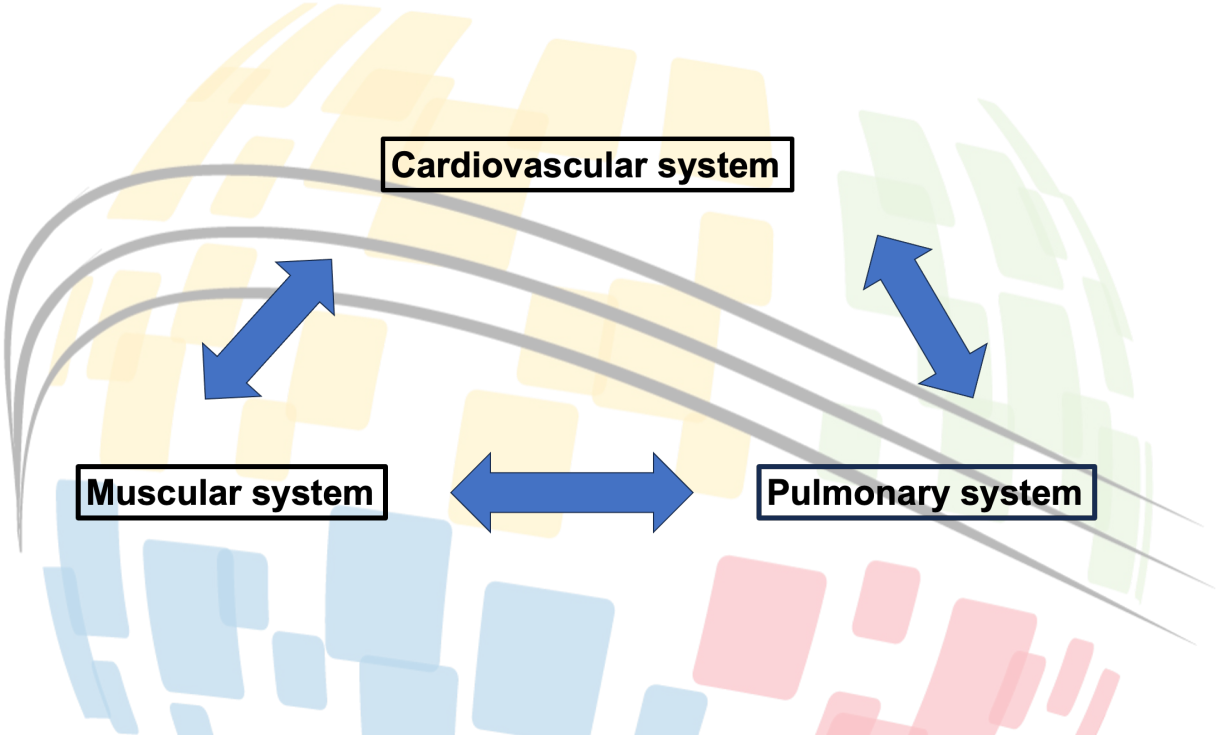
Sarwat Chappell

Senior Program Manager at Office of Naval Research
PhD Candidate at Colorado State University

Enhancing Fitness with Model Based Systems Thinking

- Benefits include improvements in movement, weight management, strengthening of bones and muscles, management and reduced risk for diseases, as well as improved brain health.
- To gain and maintain these benefits, requires a person to exercise as part of their everyday life.
- To maximize the benefit of exercise, a person must gradually increase the intensity of the exercise and maintain it at a safe level for some period of time.
- The body's ability to sustain exercise for as long as possible without injury is known as physical endurance.
- Training increases endurance and involves a change of many physiological and environmental dynamical variables that interact with each other in a complex way to modify a person's physiology over time based on an initial fitness level.

Complexity of Fitness Dynamics



- Improving fitness requires changes to many dynamical variables that interact in a complex way to generate a physical and mental change through training over a period of time.
- These factors create feedback loops that interact with each other over the training time so the cumulative effect on endurance is not evident till a runner has trained for a period of time. These loops involve the cardiovascular system, the pulmonary system, and the muscular system.
- Complexity is due to multiple reinforcing and balancing feedback loops between dynamic variables

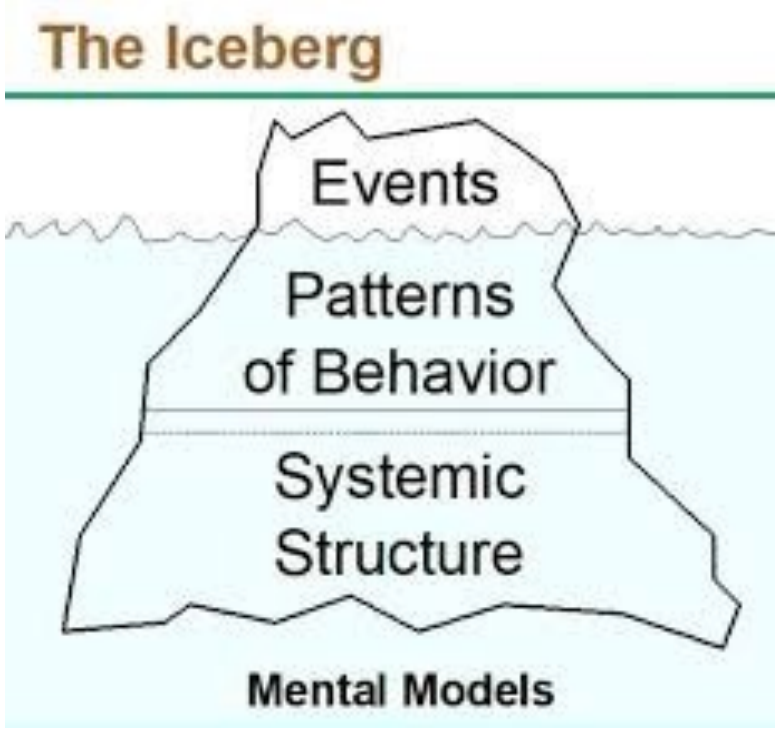
Applying the Iceberg Principle

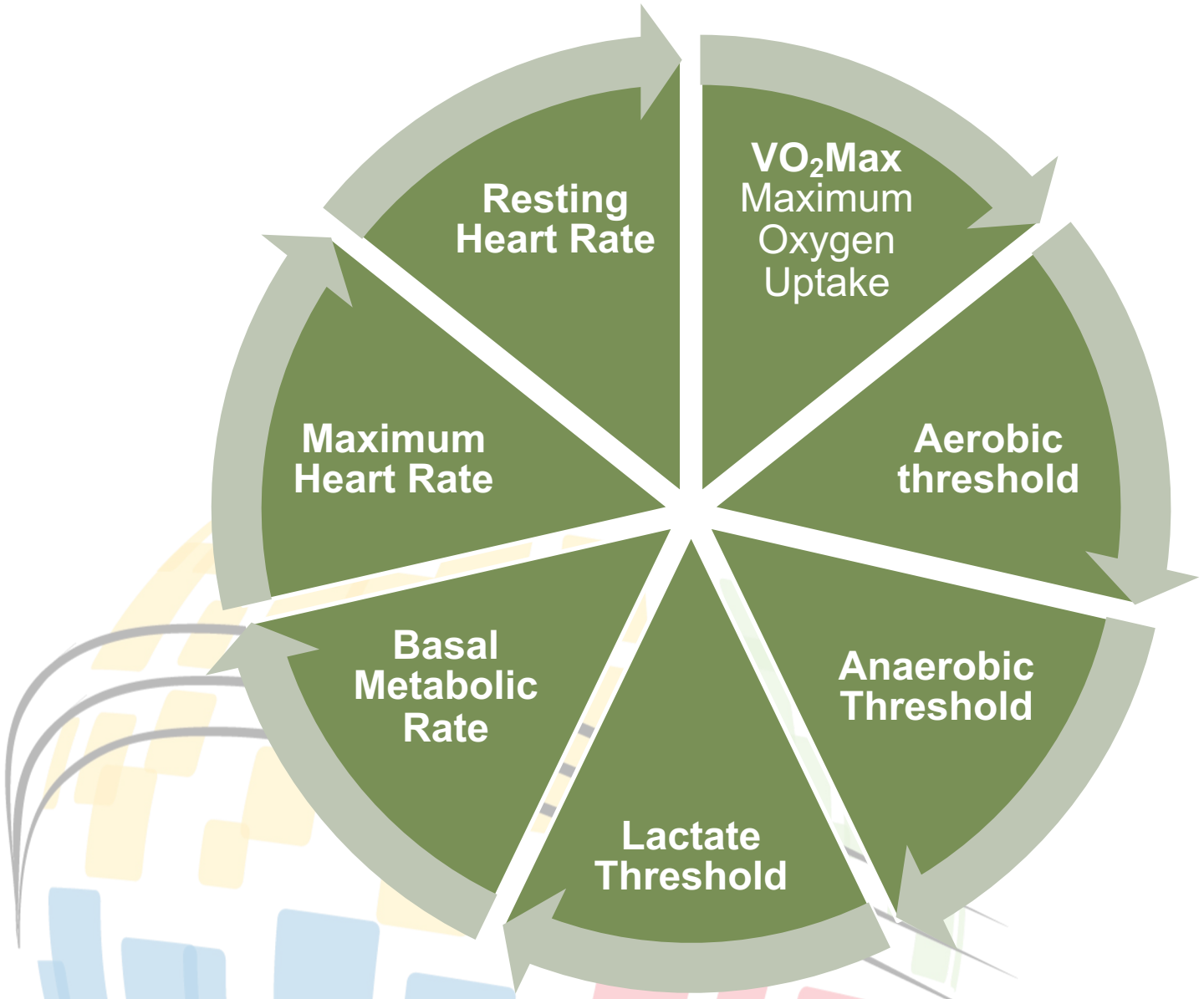
Goal achievement

Improved physiology enables better training **habits**

Training improves the physiological **structure** and state of fitness

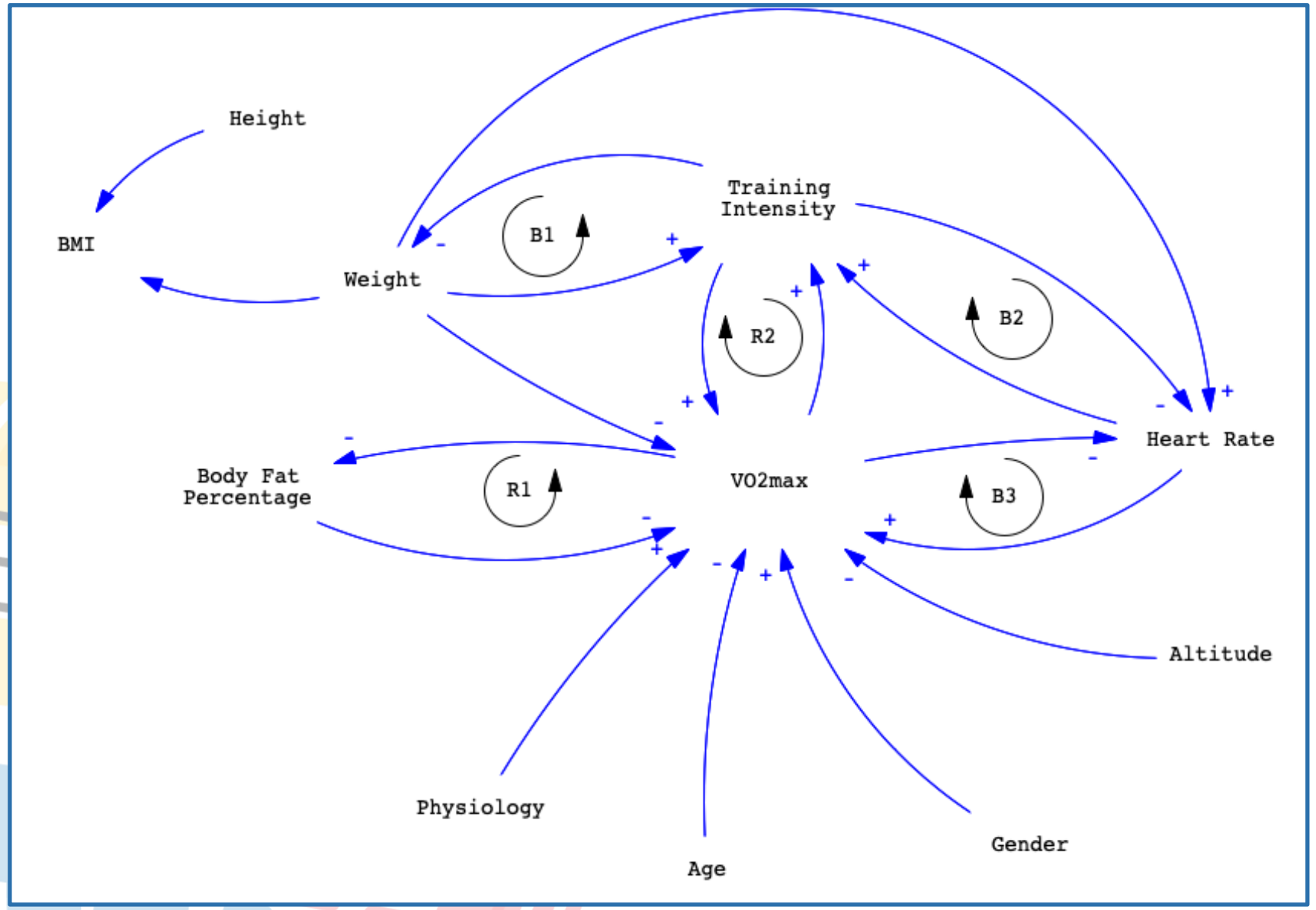
Improved fitness **mental model** enables the adjustment of training to achieve a goal based on current physiological state.



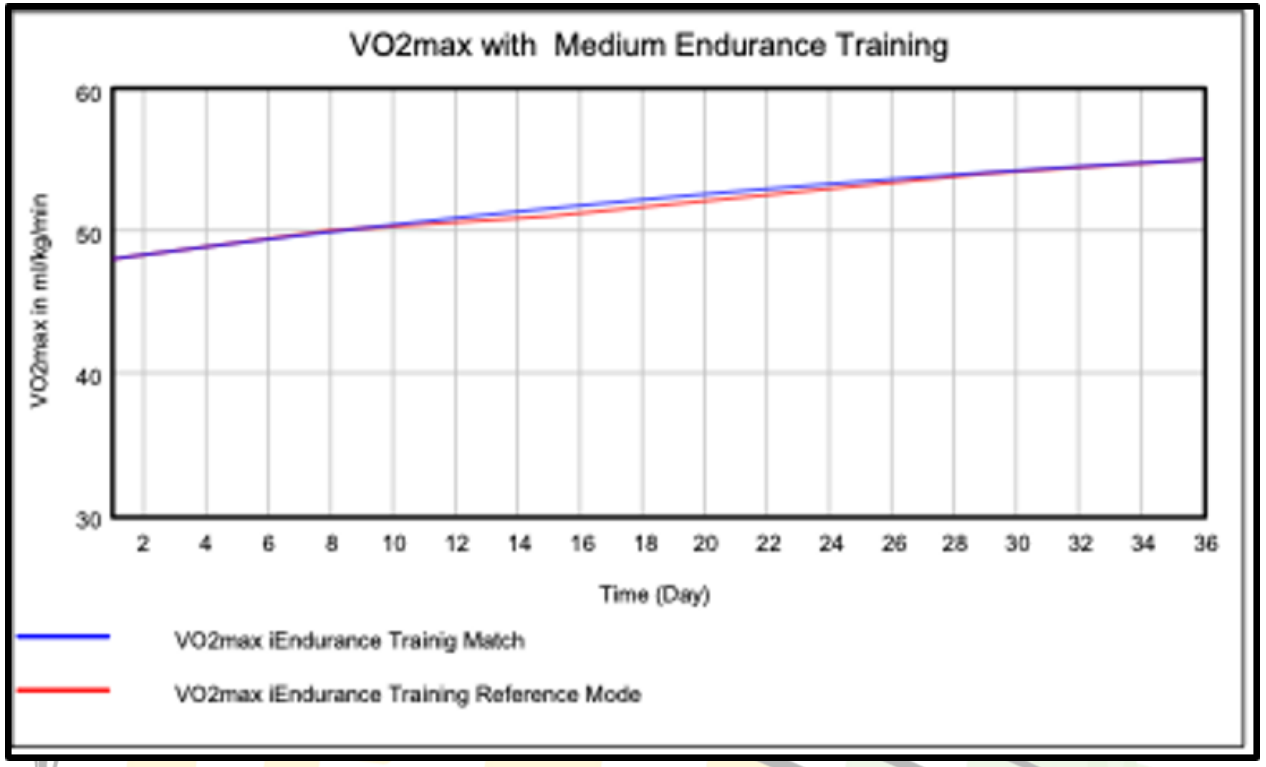


Fitness Physiology Dynamics

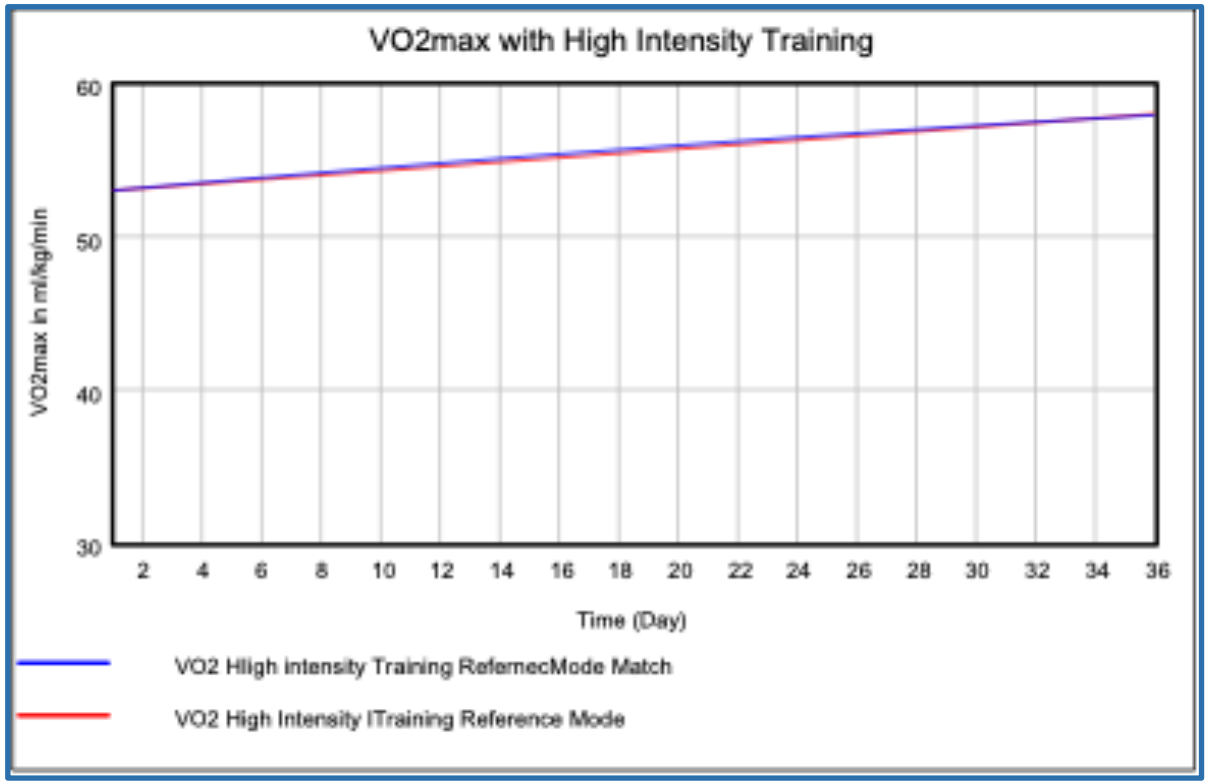
Causal Loop Diagram of Aerobic Endurance



Matched Reference Modes –VO2max

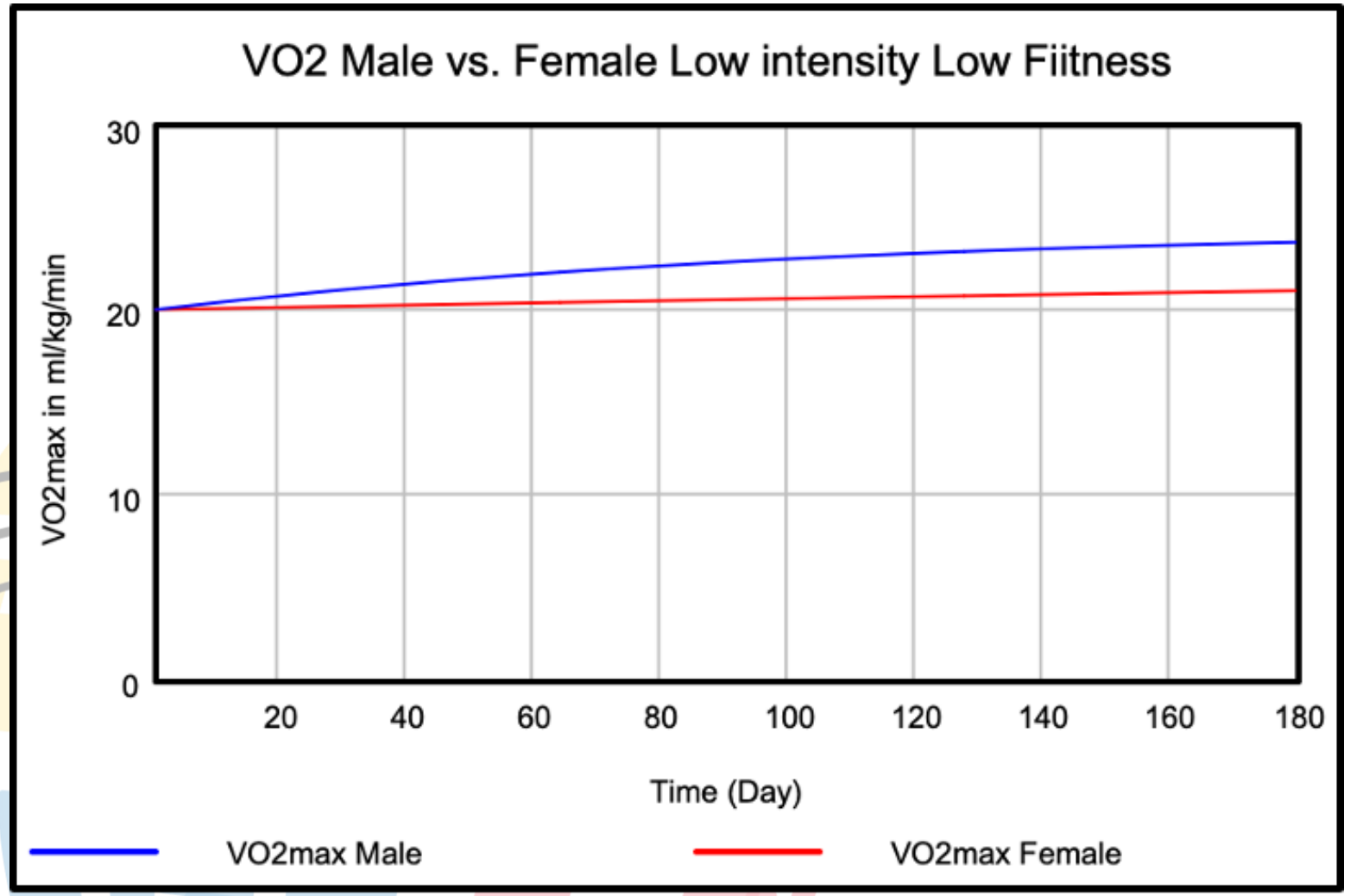


VO2max with 6 weeks of moderate endurance training



VO2max with 6 weeks of high intensity intermittent training

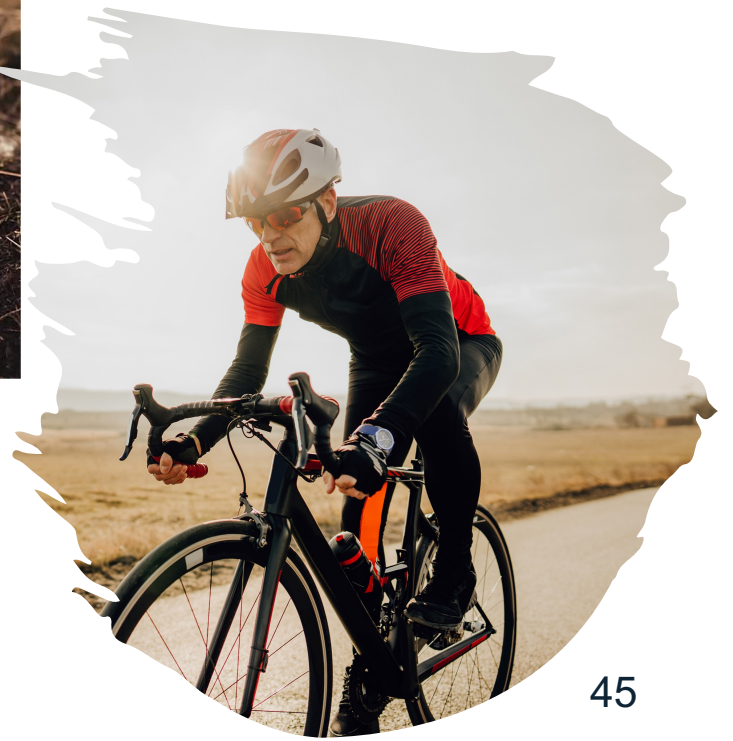
Model Prediction of Gender Difference in Vo2max Increase



Female Vo2max increases significantly lower than males for same training period

Fitness Improvement

- Holistic Approach include multiple perspectives and connects Fitness and Physiological systems with environment and other systems
- Endurance improvement is tailored to initial endurance capacity and fitness state
- Systems Dynamical Model for fitness must include non-typical factors such as Detraining, Terrain, Altitude, Weather, Diet, Recovery, Rest and Wearables.
- Real life application provides any person of any fitness level a way to improve their fitness level
- Provides health professionals, coaches a way to help people with health issues, athletes, average fitness enthusiasts and improve their fitness and endurance.



Key MBST Takeaways

- The complexity of endurance dynamics cannot be captured by linear thinking and requires the use of Model Based Systems Thinking
- Model Based Systems Thinking(MBST) provided a holistic perspective of all the variables and dynamics of endurance
- The use of rigorous tools of MBST such as the Iceberg model, Reference modes, Causal loop diagrams, causal inferences, stocks and flows, Systems Dynamics and Agent models enabled capturing the complexity of endurance dynamics and modeling of the endurance system which provides predictions.

Shall MBST be discipline agnostic or specific ?

Systems Thinking is an essential concept

Kirk Reinholtz

Retired Principal Engineer at NASA JPL
PhD Candidate at Colorado State University

Position Statement

- *Complexity:* Can't comprehend or manipulate *X* with our brains alone
  - *X* ∈ Outcome, Risks, Good and Bad Side Effects, Costs, Political resistance …
  - Complexity is in the eye of the beholder
- Risk of catastrophic consequences is growing exponentially
  - Resistance to change will increase as resources are squeezed
- Solving complex problems is the domain of SE
  - → We MUST scale our methods: Quicker development, deeper insights, larger systems
- We must see as far as we can, so that we can engineer good outcomes
  - Survival is at stake but profit/power will resist change.
  - You'll need inexorable and irrefutable logic in your pitch deck to argue for the necessary solutions and against the bad ones.
  - How? Tools. MBST.

Tools

- Fluent use of MBST tools, e.g. System Dynamics, is hard
  - A year of coursework and practice
  - Pedagogic models have a few loops. Real ones have thousands.
- But now we have ML and AI
  - Can greatly facilitate model development, refinement, analysis
  - Insights in LLM's can shed new light on your model and your SOI
- Example on next slide. Analysis of Quentins model
  - Quick - Took about 2 minutes from receipt of model
  - Easy – No claims this is amazing coding on my part. Quite the contrary
  - Goal – Critique Quentins SD model for purpose and missing loops

AI and MBST Framework

1- Start here – define the problem (Iceberg concept)

Predictability
Controllability
Reliability
Profitability

Leverage

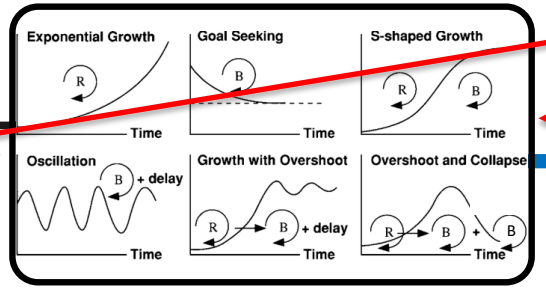
Events

Patterns

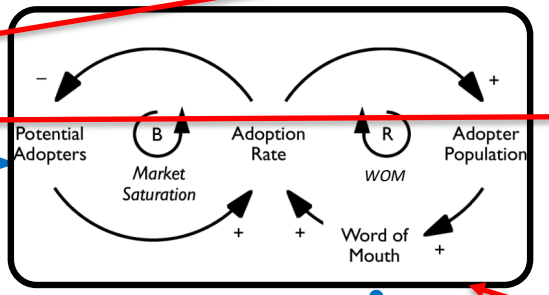
Structure

Mental Model

2 – Identify relevant patterns of behavior (Ref-modes)



3 - Develop Causal Relations (Causal Loops)



AI helps brainstorm

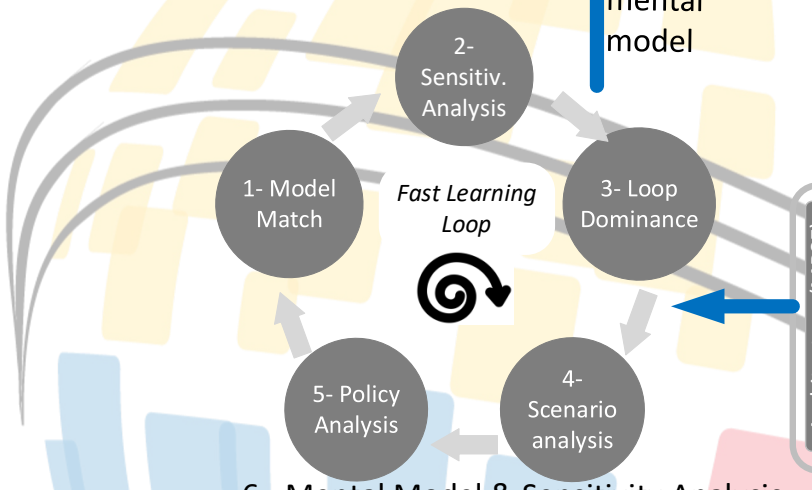
ML, AI identify basis curves

AI identifies related models, "molecules"

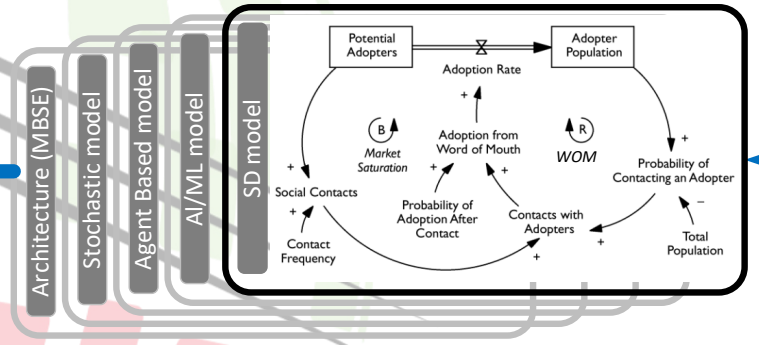
AI assists and identifies unusual usage

Update mental model

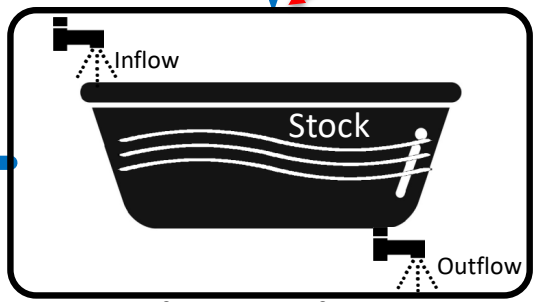
Slow Learning Loop



6- Mental Model & Sensitivity Analysis



5- Create Structure & Behavior Model



4- Classify Nature of Variables in Causal Relations (Stocks, Flows, Units)

Example: Iceberg

- A simple model generated based description of purpose of Quentins model
- Total time: about 3 minutes
- No rocket science here: Just a few prompts to focus on SD and CLD
- Suggests great potential as a “modelers assistant”

Causal Links:

- LCI increases AI
- AI increases PCI
- PCI increases PUI
- PUI increases ARI
- ARI increases NII
- NII increases LCO
- LCO increases LCI
- ARI increases MSI
- MSI increases POI
- POI decreases PUI
- POI decreases LCI

Feedback Loops:

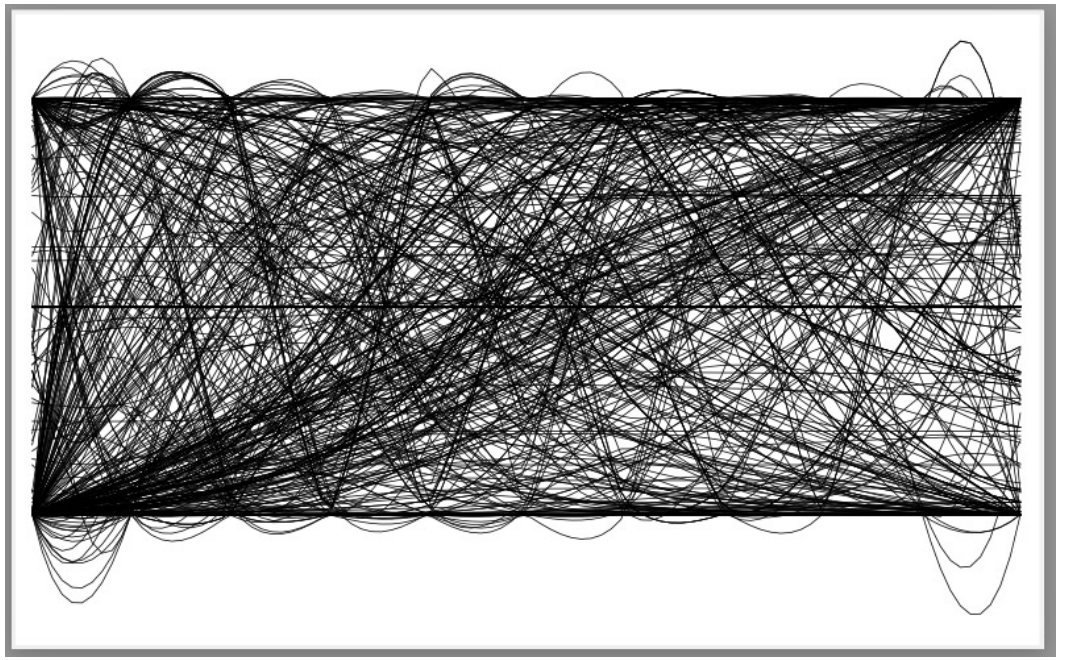
- R1: Reinforcing Loop (Positive): LCI --> AI --> PCI --> PUI --> ARI --> NII --> LCO --> LCI
- B2: Balancing Loop (Negative): ARI --> MSI --> POI --> PUI --> ARI
- B3: Balancing Loop (Negative): POI --> LCI

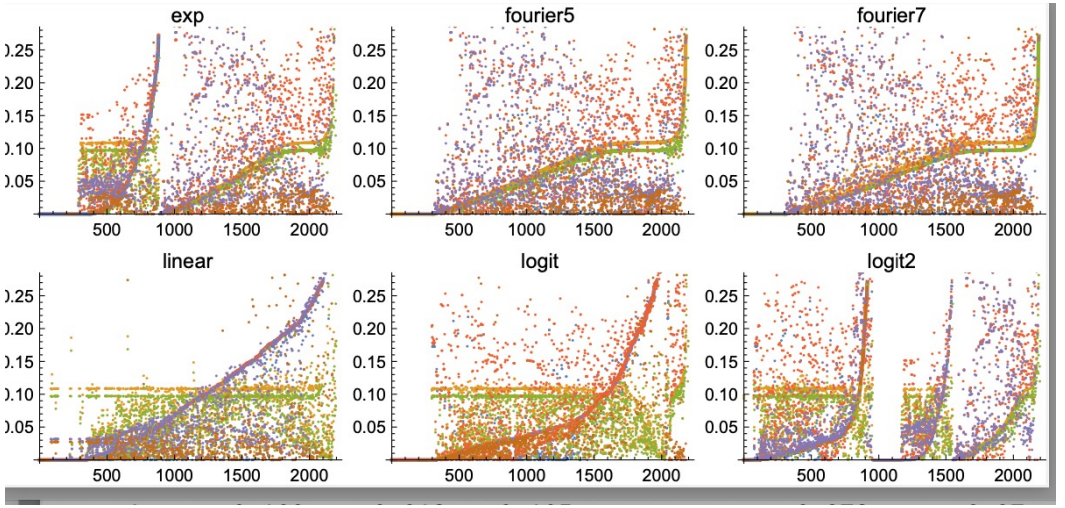
Explanation of Links and Loops:

- The initial increase in literature citations (LCI) generates more awareness of the innovation (AI), which enhances its perceived credibility (PCI).
- As the innovation is perceived as more credible, its perceived usefulness (PUI) also grows, which in turn drives the adoption rate (ARI) and leads to a greater number of implementations (NII).
- The growing number of implementations results in more literature citations of offshoots (LCO), further fueling the cycle of citations and awareness for the original innovation.
- However, as the adoption rate increases, the market for the innovation becomes saturated (MSI).
- This market saturation then leads to an increased perception that the innovation is becoming obsolete (POI).
- The perception of obsolescence negatively impacts the perceived usefulness (PUI) of the innovation, which consequently slows down the adoption rate (ARI) and reduces literature citations (LCI), thus creating a balancing effect on the system.

Example: Behavior Characterization

- Input: About 5000 curves from 1000 models
- Output: About ¾ explained by a few basis functions
- Future work: Convolve across BOTG





Example: AI Critiques Quentins model

- Given only the variables and their DAG, use AI to infer the structure and purpose of Quentins model.
- Runtime 2 minutes. Substantial setup in context window.

Purpose of model

Possible missing loops

Automatic polarity determination

Purpose of SDM: To simulate the adoption of an innovation considering the influence of relevant communities of researchers and user feedback

Potential New Variables and Units

•**Perceived Profit Potential** (unitless index or monetary units/time)
•**Perceived Power Gain** (unitless index)
•**Marketing/Lobbying Efforts** (monetary units/time or unitless effort index)

Revised Causal Relationships and Polarities

Here are some additional relationships to consider:

```
Perceived Profit Potential (+) -> Adoption Probability (+)
Perceived Power Gain (+) -> Adoption Probability (+)
Researchers That Adopted Innovation (+) -> Perceived Profit Potential (+)
Researchers That Adopted Innovation (+) -> Perceived Power Gain (+)
Perceived Profit Potential (+) -> Marketing/Lobbying Efforts (+)
Perceived Power Gain (+) -> Marketing/Lobbying Efforts (+)
Marketing/Lobbying Efforts (+) -> Researchers Exposed (+)
```

Explanation of New Relationships

•**Positive Relationships (+):**

- Higher perceived profit and power potential directly increase adoption probability.
- More adoptions signal greater potential for profit and power to others.
- Higher profit/power potential incentivizes more marketing and lobbying to influence decision-makers and promote adoption.
- Increased marketing/lobbying efforts lead to more researchers being exposed to the innovation.

Additional Causal Loops

These new relationships introduce a few more feedback loops:

1.Reinforcing Loop (R2): Researchers That Adopted Innovation -> Perceived Profit Potential -> Adoption Probability -> Researchers Adopting -> Researchers That Adopted Innovation

- This loop suggests a self-reinforcing cycle where early adopters increase perceived profit, driving further adoption.

2.Reinforcing Loop (R3): Researchers That Adopted Innovation -> Perceived Power Gain -> Adoption Probability -> Researchers Adopting -> Researchers That Adopted Innovation

- Similar to R2, but focusing on power dynamics: early adopters can consolidate their position, making adoption more attractive to others seeking power.

3.Reinforcing Loop (R4): Perceived Profit Potential -> Marketing/Lobbying Efforts -> Researchers Exposed -> Researchers Adopting -> Researchers That Adopted Innovation -> Perceived Profit Potential

- This loop highlights how profit motives can fuel marketing/lobbying campaigns, which in turn drive adoption and further reinforce the perception of profit potential.

Integrated CLD with Profit and Power Motives

The revised CLD now incorporates the original loops (R1, B1) along with the new loops (R2, R3, R4) that consider profit and power dynamics. This creates a more comprehensive and realistic model of innovation adoption.

Important Considerations

•The relative strengths of these loops will vary depending on the specific innovation, the actors involved, and the socio-economic context.
•The model still simplifies the complex interactions of profit, power, and innovation adoption, but it provides a more nuanced view than the initial version.

Summary

- SE challenges getting bigger, coming faster, and have increasing consequences
  - Human behaviors can't be ignored: Profit motive is extremely powerful
- AI and ML can help us a LOT
  - And probably the proximate cause of coming big challenges…
    - but that's another story…
- It is practical to use AI and ML to develop and comprehend models
  - Less modeling tool knowledge required: focus on problem at hand
  - Quicker model development: focus on developing and analyzing solutions
  - Deeper comprehension: Timely, effective solutions

Why is the adoption of System Dynamics so Low in Mature Industries?

- SD provides insights into behavior of technical systems
  - Behaviors generally continuous, integrable, not a lot of stochastics
- Large systems involve human behavior
  - Not just at the UI – In the C suite, politics, inter-team rivalries…
  - Each human is a hugely complex stochastic reactive system with individual characteristics
- A modeler is not likely to disaggregate behavior at required level
  - My research indicates this is virtually never done.
  - I speculate because it's technically and politically challenging, at best
- So, the model will be incomplete
  - But might inform decision processes if identifies factors decision makers missed
- Bottom Line … Lots of work, minimal impact -> limited adoption
- BUT not hopeless – AI shows promise reducing work and adding human behavior insights to SD models

Wrap-up of the discussion

Kamran Eftekhari-Shahroudi

Please share your thoughts, comments and opinions on these or related or better questions?

1. What are the rigorous frameworks, languages and tools for MBST?
2. What are some examples of real-world applications of MBST ?
3. Is System Dynamics almost synonymous with MBST ?
4. Is MBSE rigorously enabling Systems Thinking?
5. Shall MBST be discipline agnostic or discipline specific ?
6. Why is the adoption of System Dynamics or MBST so low in mature industries?

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Will use as needed

Backup

Position Statement

- Our brains can only penetrate so much complexity – And improvements will be on an evolutionary scale
- But the complexities we face and the risks thereof are growing exponentially, on time scales of months, not millennia. It will get worse as resources are ever more squeezed and bad outcomes cause worse outcomes
- Solving these complex problems while avoiding the risks is the domain of Systems Engineering. Of MBST
- We must learn to use tools routinely and intensely to see as far as we can, so that we can engineer the best outcomes available
  - Why? Because profit, power, and survival are at stake. You'll need inexorable and irrefutable logic in your slide deck to argue for the necessary solutions.

Sketch of Curriculum of ST for SE

Broad instruction in ST has been tried with limited success since the 70's. Make sure we know that history before trying again.

- Foundational MBST – Mastery of why ST is important and what it is. Familiarity with major tools. Mastery of recognizing when it should be applied.
- Critical Thinking – Systems Thinking gone wrong is Conspiracy Theory – Know the Differences
- Foundational system context – Politics and human nature
- MBST tools and theory – Augmentation of standard engineering curricula. System Dynamics, CLD, agent-based simulation, optimization, constraint satisfaction, Control Theory, Intro to nonlinear dynamics and chaos, domain-specific math and tools, statistics, ML(!), AI(!). All to level of competent user.

A.I via Big Data reaches well beyond any other tools known to date. All engineers should have substantial exposure to AI and ML combined with gigantic data volumes available today. A trillion-parameter curve fit?? Sure!