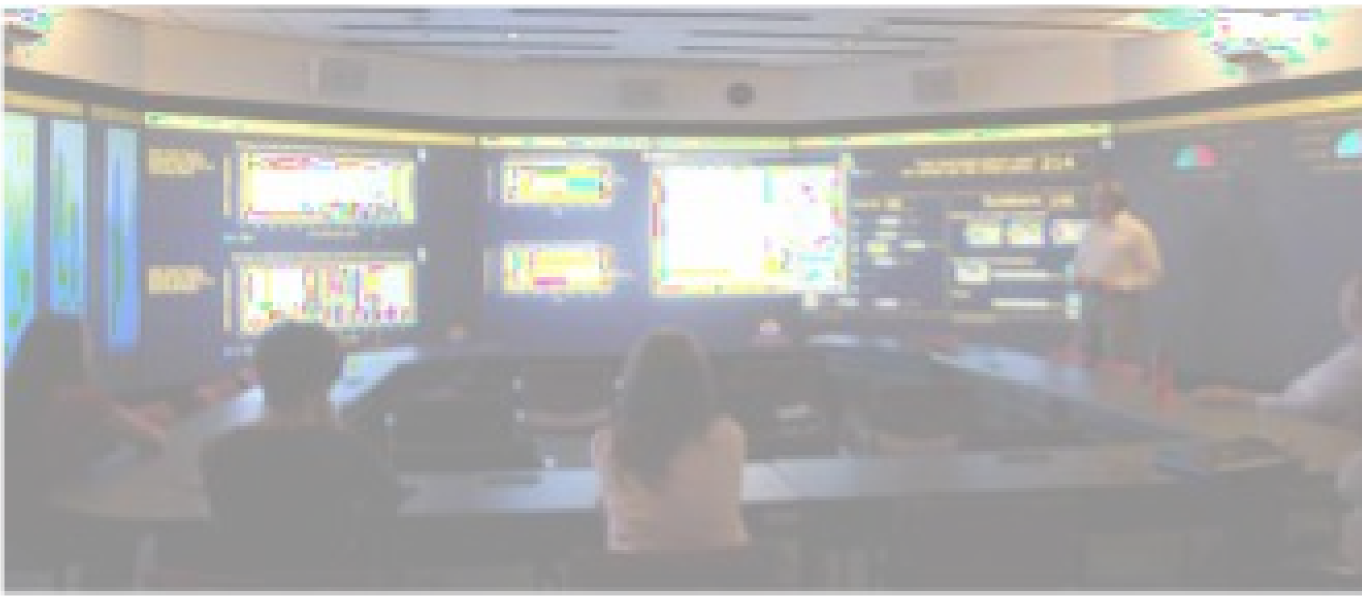
Summary: Policy Modeling Workshop

THE SOCIETY FOR MODELING & SIMULATION INTERNATIONAL™

AMERICAN UNIVERSITY
WASHINGTON, DC



Policy Modeling meets Policy Practice

A workshop during the Annual Modeling and Simulation Conference (ANNSIM) 2024, May 21, American University, Washington D.C., USA

by Prof. Dr. Petra Ahrweiler, Asst.-Prof. Dr. Taylor Anderson,
Prof. Dr. Erik W. Johnston, Prof. Dr. Thoams Clemen, Dr. Andreas Tolk

Participants representing policy practice:
Mr. Ryan A. Riccucci, Mr. Duane M Blackburn

Authors: Blanca Luque Capellas & David Wurster

Contents

Session 1

Setting the scene

Welcome by the organizers introducing the workshop idea & Presentations from policy practitioners about their background

- Prof. Dr. Thomas Clemen, Full Professor of Informatics, at HAW Hamburg, Germany
- Prof. Dr. Erik W. Johnston, Professor with the School for the Future of Innovation in Society and School for Complex Adaptive Systems, at Arizona State University
- Dr. Andreas Tolk, Chief Scientist Complex Systems Modeling at MITRE, Charlottesville
- Prof. Dr. Petra Ahrweiler, Full Professor of Sociology of Technology and Innovation, Social Simulation, at Johannes Gutenberg University Mainz, Germany
- Asst.-Prof. Dr. Taylor Anderson, Asst.-Prof of Geography & Geoinformation Science Department, at George Mason University
- **Ryan A. Riccucci** is a U.S. Customs and Border Protection agent and works a lot with modeling data to respond to (policy) people needs. Ryan is currently in the field of ontology and stresses the point, that we need to make sure that we have a common understanding when we use the same word. One of his main concerns: Why is it so difficult to get good results from the models? He thinks that at least one of the problems is the level of abstraction used to represent the knowledge embedded in the models. "Both, modeling and policy, need to understand the real world: that is where they meet."
- **Duane M. Blackburn** is Science & Technology Policy Lead, Center for Data-Driven Policy, at The MITRE Corporation and works on developing technology to support the US Department of Defense (for example, for making the aviation safer, for budget preparation, or for simulating potential threats or risks such as earthquakes). His main concern is how to deliver information to policy makers in a way it is understandable for them. He emphasizes the need of bringing the models to the people, so they can interact/engage and provide feedback to the (policy) people. To do so, "people need also to understand what models say and what they do not say." (The opening remarks from Duane Blackburn can be found in the Appendix.)

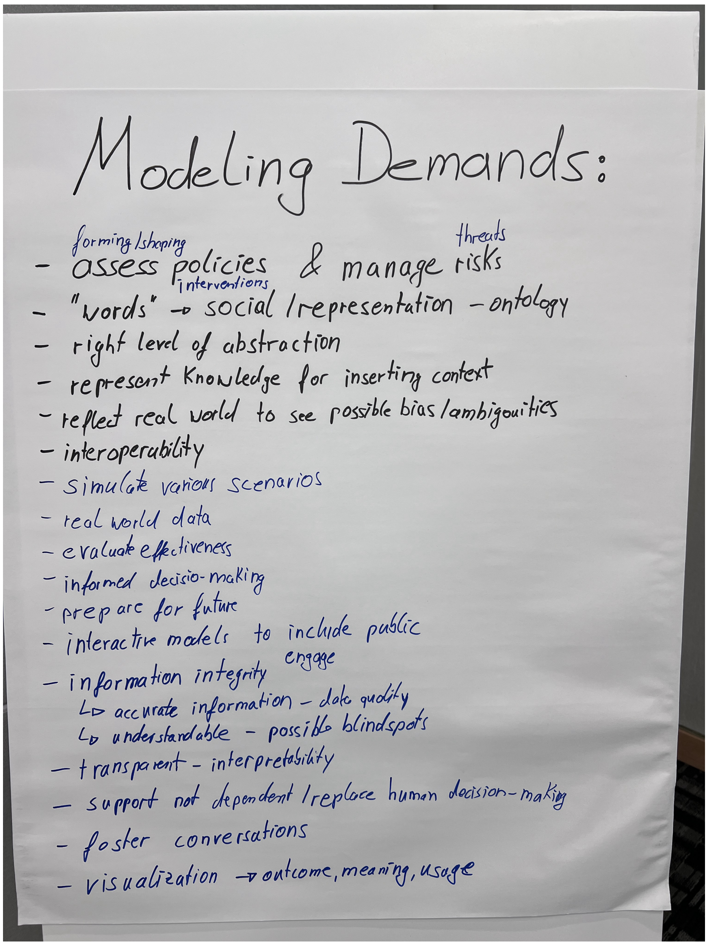
Discussion on modeling demands

- Main questions from the participants to the policy practitioners:
- Q: Sometimes models are discarded by policy people arguing there is too much uncertainty there. On the contrary, sometimes a model is accepted without checking if it is good enough just because it supports own behavior/believes.
  - A: There are some differences in using models by the industry or by the policy: Industry has more specialists while policy people are more generalists, not understanding so deeply some technical concepts.
- Q: How to communicate the limitations of the model?
  - A: Simulation is not optimization: the optimal point can change all the time, there is no a good answer. "Not to predict but to prepare for the future"

Policy demands arising: Models need to be able to…

- form/shape/assess policies/policy interventions, to manage possible risks/threats
- emphasize on ontology to better represent the real world context of the model
- have the right level of abstraction.
- represent knowledge about the context of the model.
- reflect real world to see possible bias/ambiguities
- be interoperable.
- simulate various scenarios.
- handle/work with real world data
- evaluate the effectiveness of interventions/various scenarios.
- support informed decision-making
- prepare us/society for better future
- be interactive to ensure inclusion/engagement with wider public (the public understands complex issues, and the policy people receive feedback from citizens)
- emphasize on information integrity, which means the models work with accurate data (data quality), as well as are understandable (what does the model show, and what it´s not, blind-spot)
- be transparent and interpretable
- support policy makers (not try to replace them, or be dependent on them).
- visualize three things: Outcome, Meaning (of the outcome), Usage (possible actions/advise for/to policy practitioners)

(Picture from modeling demands from policy practitioners created during the workshop)



Session 2

Practices in Policy Modeling

- The portfolio of policy modeling and simulation methods: What is on the offer, how does it work, and what works best?

Talk: Best Practices in Policy Modeling: Curiosity, Inclusion, and Empathy

By: Prof. Dr. Erik W. Johnston, Arizona State University, US, erik.johnston@asu.edu

1. Curiosity

Models are more oriented to answer questions than to ask better questions.

Example: public transport design in Arizona. Process to allow people to think in terms of systems.

Challenge:
How do we get the powerful to be curious?

Lessons:

- ➢ To engineer curiosity, the "Trojan Horse" approach is useful for translational research.
- ➢ Policy makers are far more likely to act on something that they have discovered themselves.

2. Inclusion

- People are more likely to use systems/models they created themselves.
- Include more diverse perspectives
- Leverage both top down and bottom up strategies (collective/individual level)
- Resilience, heat vulnerability and many other challenges are shared challenges
- Support self-organizing with models according to local conditions: inclusion of different realities

Lesson:

➢ focus stacking

1. What is the **scale** of the problem that you are trying to solve
2. **Discipline**: Depending on your discipline, you often are trying to solve questions arising within that discipline
3. **Parts of the system:** include all parts/stakeholders/organizations of the system
4. **Uses of the system:** Example of a gym – one model could be used for different uses

3. Empathy

- Relationship building is important, reach out to the community your model is built for
- Higher empathy leads to better solutions and better outcomes.

Lesson:

- A well developed capacity for empathy and kindness is a deep form of strength. Understanding the role of empathy opens up new models and practices pf collaboration. Humility is a valuable trait in a modeler.

4. Takeaways

- Challenge is to design inclusive governance infrastructures to detect, deliberate, and discover in support opportunities for diverse communities in support of their own values
- For further information, see "**A Knowledge Exchange Playbook to Build Resilience**" Link

Challenges for Policy Modeling and Policy Support: A Simulationists´ Perspective

- Defining a research agenda from the point of view of the research community.
- By: Prof. Dr. Thomas Clemen, HAW Hamburg, thomas.clemen@haw-hamburg.de,
  Dr. Andreas Tolk, The MITRE Corporation, atolk@mitre.org

1. Simple, Complicated, and Complex Systems and Policy Makers

—> "We are living in a very complex world and it is all about people."

2. Political decision support – past and present

- Oracle of Delphi vs. (policy) advisers within(federal) ministries

Key questions:

- How political decision support systems look like/should work in the future?
- Do we need another oracle, and if so, how can we create it?

3. The Evolution of Agent-based Simulation models

1. Past: Rule-based agents
2. Current: Intelligent Learning Adaptive Agents
3. Future: Cooperative, Collaborative, Competitive Agents, …?

Key questions:

- What degree of complexity for which problem?
- How many agents are required?

4. Where are we as Simulation Experts?

- How to visualize points of no return?
- How to visualize uncertainty?
- We need to visualize different perspectives at the same time.
- Not prediciting, but showing and visualizing what could happen and be a possible scenario.

5. Participative Modeling:

- How to make people do modeling who do not do modeling?
- No model should be done without the modeled!
- All social groups understand the diverse challenges, options considered, and proposed solutions

—

Thomas & Andreas created a small survey to get your feedback: [Link to survey]

Questions within survey:

1. Imagine you had the opportunity to consult a political advisory oracle. What questions would you ask it?
2. Which current developments in the fields of simulation, AI and other disciplines have the greatest impact on policy advice?

Session 3

Policy Modeling Examples

THE INFSO-SKIN MODEL

Prof. Dr. Petra Ahrweiler, Johannes Gutenberg- University Mainz, Germany
petra.ahrweiler@uni-mainz.de

- European research funding (European Commission)
- Impact assessment and ex-ante evaluation, in 2014, of the Horizon 2020 (European Framework Program 2020-2024)
- SKIN model (an agent-based simulation platform) was applied. The model includes knowledge, actors, and networks.
- Certain questions:
  - What if there are no changes between FP7 and Horizon 2020 policies?
  - What if there are changes to the thematic areas?
  - What if there are changes to the instruments of funding?
  - And so on…
- The study was presented before Horizon 2020 started and it was approved for policy makers.
- **Lessons learned from stakeholder co-design:**
  - Identification of stakeholders questions.
  - Data requirements: what data do the stakeholders have?
  - Validity check with stakeholders.
  - Visualizations.
  - Discussing scope and limitations.

Analyzing Transport Policies in Developing Countries with ABM

Kathleen Salazar-Serna, Pontificia Universidad Javeriana – Cali, Colombia,
kathleen.salazar@javerianacali.edu.co, kgsalaza@unal.edu.co

- Model that could be used to analyze emerging behaviors: distribution of transport users
- Analyze policy impacts in terms of CO2 emissions, road accidents, average speed and travel time during the peak hour
- The model calculates:
  - strategies to make decisions, based on individual satisfaction, uncertainty and individual thresholds
- You can use the model for an initial Setup, Experiments, or Policy analysis
- Policies that can be evaluated so far:
  - Cost-related policies, Capacity, Personal security perception
- Challenges: information gathering and low interest from local authorities.
- **Lessons learned:**
  - From the modeling process…
    - The availability of information.
    - Balance between theoretical and empirical models is crucial.
    - Customization of existing models according to the context is important.
    - Sociocultural aspects influence the behavior of the system.
  - From the results…
    - The system has a lot of inertia, thus, it is difficult to generate significant changes through feasible policies.
    - Policies aimed at only one factor are less effective than those directed at multiple factors.

Simulation for Policy Decision Support – An Opioid Example

Dr. Andreas Tolk, The MITRE Corporation, atolk@mitre.org

- Artificial Societies Integrative Platform.
  - The model includes synthetic Data from RTI and MITRE´s SYNTHEA, as well as Survey & Administrative Data (CDC, DC Government)
  - The model consists of
    - 560,000 Individuals
    - 51,000 workplaces
    - 260,000 Households
    - 200 schools
- The model can simulate the deaths attributed to opioids as a result based on effects of absence, presence, and active support from social networks
- Consistency & Plausability: the model predicted, that if the government would close workplaces and schools, a huge increase of deaths related to opioid could happen. Unfortunately it was the case during the COVID pandemic.

Modeling patterns of life in urban areas

Sandro M. Reia, George Mason University, Fairfax, Virginia, US, smarti71@gmu.edu

- The model is a large-scale agent-based model that is easily transferable to study human mobility and its impacts on processes taking place in urban areas.
- The model is:
  - Needs driven: The model is based on a Maslow-like hierarchy of needs, triggering behaviors in agents to perform tasks that satisfy their needs.
  - Scalable: The model is optimized in the Repast4Py ABM framework to address the challenge of scalability (1 million agents ~ 3 mins per day).
  - Tunable: The model facilitates the exploration of research questions regarding mobility patterns.
  - Transferable: We use publicly available datasets to easily transfer the model from one city to another.
- Application for policy and decision support:
  - Characterization of urban mobility in data scarce areas.
  - Characterization of impacts caused by local disruptions.
  - Heterogeneous dynamics of epidemic spreading.

SmartOpenHamburg - A system to support decisions in urban policy

Prof. Dr. Thomas Clemen, HAW Hamburg & The MARS Group, Germany, thomas.clemen@haw-hamburg.de

- The goal of the model is to become a large-scale Digital Shadow/Twin of the City of Hamburg
- The model does/performs/simulates
  - Integration of IoT real-time data
  - Set up scenarios quickly
  - Flexible integration of GIS data objects
  - Up to 2 Mio human agents
- Idea: 5 minutes walking from one transport to the other in the whole city.
- Goal: connect the simulation model to the urban data platform and IoT sensor network; set up scenarios quickly
- Applications of the SmartOpenHamburg Model are several, and many options are opened since the City of Hamburg funds the project. E.g.
  - Planning support for the so-called traffic turnaround, e.g., a basis for the introduction of new metro and bus lines
  - Logistics, e.g., mixing delivery trucks and buses
  - Decision support for police and fire department operations (safety and security issues), e.g., police operations, demonstrations, evacuations, etc.,
  - Modeling the spread of infectious diseases and public health

Feedback from Policy Practitioners point of view on lightening talks

Duane M. Blackburn, Science & Technology Policy Lead, Center for Data-Driven Policy, The MITRE Corporation

- Considerations for modelers:
  - Policy people don't care about how the project was designed or run: they care about the results and how useful they are. They don't have time for getting so much information about the project process.
  - Policy people don't care about publications, it means the work was done/performed already months, or even years ago. Policy people expect to listen to something new, that no body else knows.
  - Images used in a presentation for policy people should support what is being said. Otherwise they become a distraction: in this case, better not to include images.

Session 4

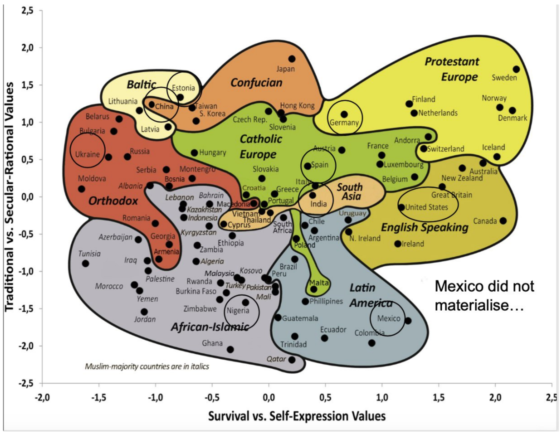
Using Artificial Intelligence for Welfare Decisions: A Policy Modeling Pilot

Talk: USING ABM AND SERIOUS GAMES TO CREATE "BETTER AI", AI-based assessment for public social service provision

By: Prof. Dr. Petra Ahrweiler, Johannes Gutenberg- University Mainz, Germany
petra.ahrweiler@uni-mainz.de

- Artificial Intelligence for Assessment (AI FORA) project. – Question: How to develop policies for contextualized, value-sensitive, responsive and dynamic AI systems using simulation models?
- Context:
  - AI assessing people is being implemented worldwide for assigning social benefits to those who need/deserve them.
  - What does "fair" mean in different social contexts in this frame?
  - Ethical concerns arise: efficiency, objectivity, bias, fairness, among others.
- AI FORA seeks to develop "better AI" for social assessment using a participatory approach.
  - The point is turned: People assessing and shaping AI (technology and innovation assessment).
  - Social benefits distribution (who gets what from the state) concerns everybody, being recipient, policy maker, or tax payer. —> Everybody is a stakeholder for innovation.
- Cultural values and social context are key.
  - What is fair in different cultural contexts?

- AI FORA includes case studies in many different countries: Spain, Estonia, Germany, USA, India, China, Ukraine, Iran, Nigeria.



- AI FORA works with vulnerable groups using a "Safe Spaces" concept.
  - "Loosers" as experts: Those who fall through the net or do not benefit, are those who can provide the most competent information about the injustices, failures and shortcomings of existing social assessment system.
  - Empowerment is necessary. —> "Safe spaces" concept developed.
- No fair training data for AI is produced. Therefore, it is necessary to co-produce context-dependent, value-sensitive, responsive and dynamic AI systems. Process developed to create "better AI":
  - Ruleset 1: How does the current AI system works?
  - Participatory deliberation from existing to desired systems, through gamification, negotiation, learning.
  - Ruleset 2 is created: better ruleset to ganerate new training dataset.
  - Machine training with the new "better ruleset" data.
- What an ABM in AI FORA policy modeling is good for?
  - Co-designing AI systems with stakeholders.
  - Ex-ante evaluation for testing and prototyping AI systems before implementation.
  - Scenario analysis and what-if questions to reduce uncertainty.
  - Directly create training data, e.g. using a micro simulation approach, reducing process complexity.
- Upcoming policy workshop of German case study at the EWAF Conference, Mainz (Germany), July 1-3, 2024.
- Results will be published soon in a Springer book: "AI Assessing People for Receiving Public Social Goods".

Lessons learned:

- Since the public resources are scarce, a bias will be always present to decide who deserves/needs social benefits. What is needed is a bias widely and culturally accepted into each culture.
- "Loosers" are those thrown through the net: the ones who did not get the social benefits support. Since they are not in a position of being heard, a participatory approach with a "safe spaces"concept is needed. Although they don't have a better perspective, they can provide very valuable to be considered about the system.
- During the model-building process more information is discovered than after the model is built and runs.

Insights and lessons learned from the AI FORA US case study

By: Prof. Erik Johnston PhD, Arizona State University, Tempe, AZ. (USA)
erik.johnston@asu.edu

- AI FORA US case study research focuses on social care/service provision in Illinois.

Lessons learned:

- Cultural mirroring: The people administrating the system is quite different from people being beneficiary of the system.
- The bias comes from different source, such as data biases and algorithmic biases, among others.

Session 5

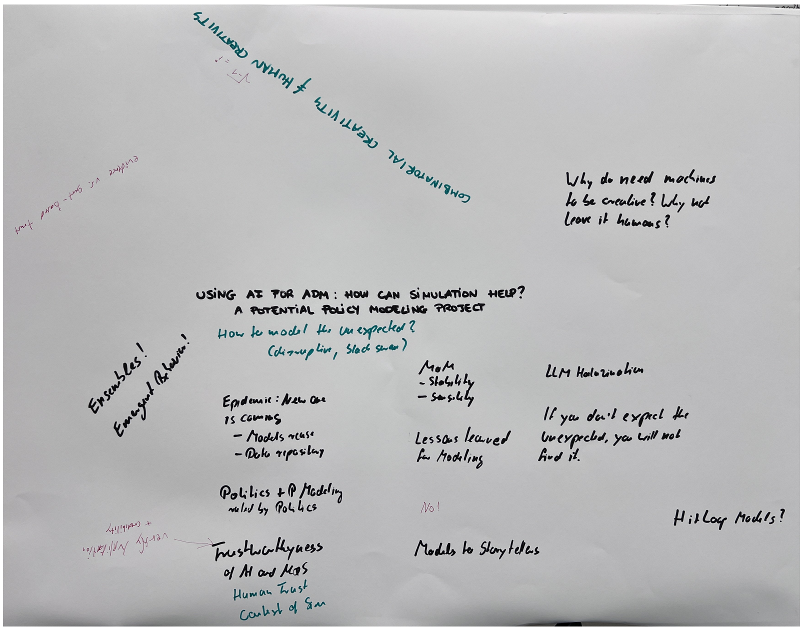
Using Artificial Intelligence for automated decision making in any policy domain (terrorism recidivism, unmanned drones, granting asylum etc.)

- Create your own participatory policy modeling project (Co-creation process among policy practitioners and modelers)

The task for the workshop participants is to do a 45 min world-café (15 min per table) to discuss using Artificial Intelligence for automated decision making in the three chosen policy domains along the following question:

- **Using AI for ADM: How can Simulation help? A potential policy modeling project:**

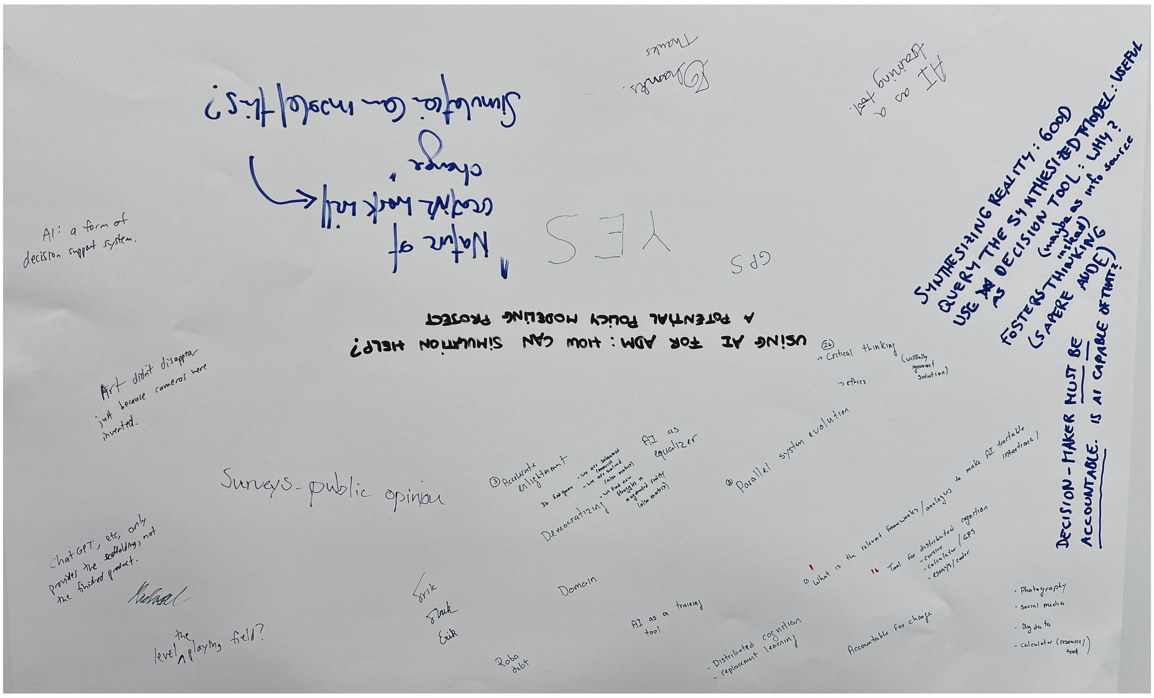
Table A – Hosted by Dr. Andreas Tolk



Summary Table A:

- **How to model the unexpected? (disruption, black swan)**
- Epidemic: New one is coming
  - Models reuse
  - Data repository
- Politics + PModeling ruled by Politics
- Trustworthyness of AI and Models
  - Verify replication, credibility
- MoM; Stability, Sensibility
- Lessons learned for Modeling
- Models to Story tellers
- Human trust context of Simulation
- Why do need machines to be creative? Why not leave it humans?
- Ensembles! Emergent Behaviour!
- LLM Haluzination
- If you don´t expect the unexpected, you will not find it.
- Combinatorial creativity unequal Human creativity
- Evidence vs. gut-based trust
- Hitloop Models?

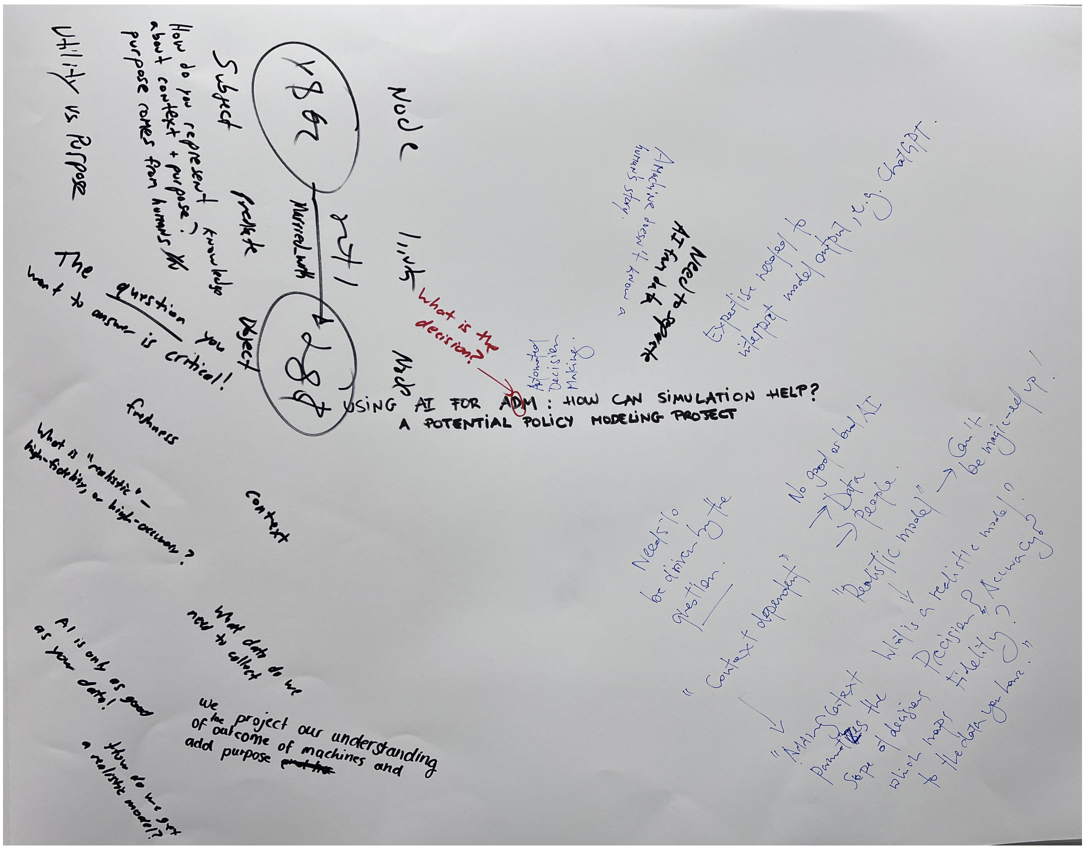
Table B – Hosted by: Prof. Dr. Erik W. Johnston



Summary Table B:

- **What are the relevant fameworks/analogues to make AI tractable/intetnionel**
- Tool for distributed cognition
  - Cursive, calculator/GPS, essays/coder
- Photography, social media, Big Data, calculator (resources/tool)
- Art did´nt disappear just because cameras were invented
- Accountabel for change
- Distributed cognition, replacement learning
- Robo debt
- AI: a form of decision support system
- „Nature of creativity work will change“ – Simulation can model this?
- **Parallel system evolution**
- Critical thinking (ethics)
- **Accelerate enlightment**
- Levels the playing field
- ChatGPT, etx. Only provides the scaffolding, not the finished product
- AI as a training tool
- Surveys- public opinion
- Democratizing

Table C – Hosted by Mr. Ryan A. Riccucci



Summary Table C:

- Freshness & Context
- Context-dependent
- Adding context parametrizes scope of decisions, which traps to the data you have
- We project our understanding of the outcome of machines and add purpose
- Utility vs. Purpose
- What data do we need to collect
- AI is only as good as your data
- How do we get a realistic model?
    - What is “realistic” – high-fidelity, or high accuracy? Precision, Accuracy, Fidelity?
    - Can not be magic-set-up
- The **question** you want to answer is critical
- Needs to be driven by the question
- No good or bad AI
    - Data & People
- Expertise needed to interpret model output, e.g. ChatGPT
- Need to separate AI from Data
- A machine does not know a humans story
- How do you represent knowledge about context and purpose? Purpose comes from humans.

Session 6

Closing Panel: Evaluation by Practice and future Opportunities

- Assessment of utility of cutting-edge policy modeling activities: Feedback from policy practice
- Presentation of world-café results by table hosts/chairs

Appendix

Opening Remarks at 2024 Annual Modeling and Simulation Conference - Policy Modeling Meets Policy Practice by Duane Blackburn

„Modeling in Policymaking
I have had the privilege of working in the White House, tackling policy issues at the highest levels of our federal government, and have seen the value of computational models in informing and shaping policy decisions.

Modeling has been an aspect of policymaking for many years. It has been used to support a wide range of complex issues, from economic forecasting to national security and public health.

Take, for example, the use of economic models in budget preparation. These models are used to forecast economic indicators such as GDP growth, unemployment rates, and inflation. They help policymakers understand the potential impacts of different fiscal policies and make informed decisions about government income and spending.

Similarly, in the realm of national security, models have been used to simulate potential threats and assess the effectiveness of various defense strategies. They help us understand the potential consequences of different actions and make decisions that protect our national interests while minimizing risks.

In the context of public health, models played a critical role in our response to the COVID-19 pandemic. They were used to predict the spread of the virus, assess the impact of different mitigation strategies, and inform decisions about lockdowns, travel restrictions, and vaccine distribution.

An important area that isn't often considered by the public is continuity of operations, or COOP. Activities here help ensure that agencies are able to continue performance of essential functions under a broad range of circumstances. Modeling is used to simulate various scenarios that could disrupt normal operations, such as natural disasters, terrorist attacks, or cyber threats. These activities help us understand the potential impacts of these disruptions, assess the resilience of our systems and processes, and identify areas for improvement.

- For example, we might use a model to simulate the impact of a major earthquake on the operations of a federal agency. The model would take into account factors such as the location and magnitude of the earthquake, the structural integrity of the agency's buildings, and the availability of backup systems and resources. The results of the model would help us understand the potential risks to the agency's operations and inform decisions about emergency preparedness and response.
- Similarly, in the realm of cybersecurity, models are used to simulate cyber attacks and assess the robustness of our IT systems. These models help us understand the potential vulnerabilities in our systems, evaluate the effectiveness of our security measures, and inform decisions about IT investments and policies.
- In these cases, the goal of modeling is not to predict the future with certainty, but to prepare for it. By simulating different scenarios and understanding their potential impacts, we can make informed decisions that enhance the resilience of our operations and ensure the continuity of essential functions under a broad range of circumstances.

These are just a few examples of how modeling has been used in White House-level policymaking. They illustrate the power of models to handle complex systems, analyze vast amounts of data, and provide insights that inform policy decisions.

Increasing Modeling in Policymaking
Now, let's explore how the use of modeling could be beneficially increased in policymaking.

First, there is a significant opportunity to broaden the use of modeling in areas where it is currently underutilized. For instance, in social policy areas, modeling could be used to predict the impacts of different policy interventions, identify the most cost-effective strategies, and understand the complex interactions between different factors.

For example, in law enforcement, predictive policing models could be developed to anticipate crime hotspots and inform the allocation of resources. Similarly, in homeland security, models could be used to simulate the impacts of different threat scenarios and inform decisions about resource allocation and emergency response strategies. Both are being done to some degree, but could be enhanced.

Second, with the advent of more advanced computational techniques and the availability of larger and more detailed datasets, there is potential to develop more sophisticated and accurate models. These models could provide deeper insights into complex policy issues and enable more precise predictions of policy outcomes.

- For example, in the realm of Science and Technology policy, advanced models could be used to forecast trends of critical and emerging technologies, assess the potential impacts of different policy interventions, and inform decisions about research funding and regulation as we struggle to stay ahead of China in the international S&T competition – but doing so in a way that aligns with international norms and American values.

Third, there is potential to use modeling to enhance public engagement in policymaking. Interactive models could be used to help the public understand complex policy issues, explore different policy options, and provide feedback on proposed policies. This could lead to more informed and inclusive policy debates.

Finally, there is an opportunity to use modeling to improve the transparency and accountability of policymaking. By making the models and data used in policymaking publicly available, we can enable independent scrutiny of policy decisions and provide clear, data-driven justifications for our actions.

Challenges of modeling in policymaking
Finally, let's delve into some of the issues that are most concerning about increased modeling use.

First, and foremost in my mind, is the issue of information integrity. Models, even those that are poorly or incorrectly developed, provide 'evidence' that can be used in policymaking or in advocacy for preferred policy positions. This can lead to misinformation (incorrect information unknowingly shared), disinformation (deliberately shared false information) and malinformation (superficially accurate info presented without needed context to misinform). It's therefore critical that modelers proactively explain the results, and the limitations of those results, in a way that anyone can readily understand.

This is not just about ensuring that information from models is accurate, but also about ensuring that it is used appropriately and responsibly. Policymakers and the public need to understand not just what the models say, but also what they don't say, and what assumptions and uncertainties they involve. In the policymaking space, this is of utmost importance. But I rarely see much focus on it from modeling scientists. Don't let others, with bad intentions or poor understanding of modeling science, do it for you.

Second, there is the issue of data quality. Bad data can lead to bad decisions, even with good models. It's crucial that we have robust processes in place to ensure the quality and reliability of the data that is used in our models.

Third is the issue of AI safety and assurance. As we increasingly use AI in our models, we need to ensure that we understand how it works, how to properly use its outcomes, and how to manage the risks it presents. This includes risks related to interpretability, transparency, accountability, and cybersecurity.

- For example, AI models, particularly those based on complex machine learning algorithms, can be incredibly powerful and accurate. However, they can also be opaque, with the decision-making process hidden within layers of computations. This is often referred to as the "black box" problem: we can see the inputs and the outputs, but the process in between is hidden from view and not understood. This lack of interpretability can be a significant issue in policymaking. If we don't understand how a model is making its predictions, it can be difficult to trust those predictions or to justify policy decisions based on them.

Finally, there is the issue of dependence on technology. An over-reliance on advanced models for policymaking can risk sidelining human oversight and judgement. It's crucial to remember that models are tools designed to support, not supplant, human decision-makers. While models can provide valuable insights and predictions, they cannot replace the nuanced understanding, experience, and ethical judgement that human decision-makers bring to the table.

In fact, human decision-makers are not just part of the loop, they are at the very heart of it. They are the ones who define the questions that the models seek to answer, interpret the results in the context of broader policy goals and societal values, and make the final decisions based on a combination of model outputs, other evidence, and their own judgement.

Models can inform and guide decision-making, but they cannot make decisions. That responsibility lies with human policymakers, who must balance the insights from models with a range of other considerations, including ethical, political, and practical factors.

In Conclusion

As we have explored today, computational modeling holds immense potential to inform and enhance policymaking at the highest levels of government. It can provide valuable insights into complex issues, predict the impacts of different policy interventions, and support more informed, effective, and equitable decision-making.

However, as we embrace the power of modeling, we must also be mindful of the challenges it presents. We must ensure the integrity of the information our models produce and how they will be used, the quality of the data they rely on, and the safety and transparency of the AI techniques they employ. Most importantly, we must remember that models are tools to support human decision-makers, not to replace them.

As we stand at the intersection of policy and advancing technological capabilities, we have a unique opportunity - and responsibility - to shape the future of modeling-enabled policymaking. To seize this opportunity, we must foster a dialogue between modelers and policymakers, between the world of numbers and the world of people. We must ensure that our models reflect the complexity and diversity of the societies they aim to serve, and that they are used in a way that respects our values and serves our common goals.

In the end, the power of modeling lies not in the data it produces, but in the conversations it sparks, the understanding it fosters, and the decisions it informs. Thank you.“