How to escape the dilemmas of complex systems modelling in public health

A users guide and map

Brian Castellani

Research Methods Centre and Wolfson Research Institute of Health and Wellbeing, Durham University, UK

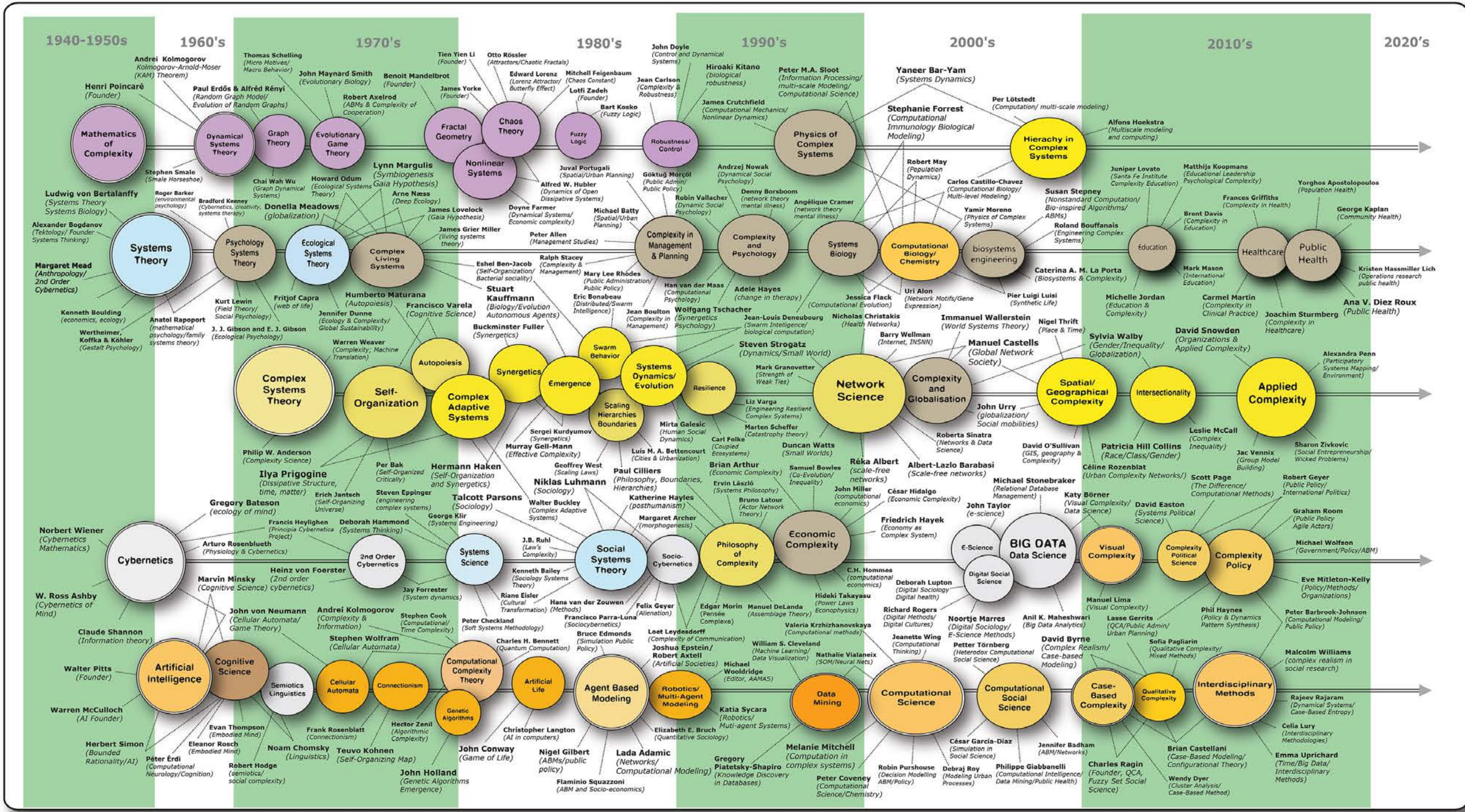
Much thanks to Corinna and team for putting this conference together and for the opportunity to provide this talk today.

Early career researchers and postgraduates . . .
Hang in there!

University of Glasgow, 4-8th September 2023.

The conference is one of the key activities of the **European Social Simulation Association (ESSA)** to promote social simulation and computational social science in Europe and elsewhere.

MRC/CSO Social and Public Health Sciences Unit



1940-1950s
1960's
1970's
1980's
1990's
2000's
2010's
2020's
Mathematics of Complexity
Henri Poincaré (Founder)
Andrei Kolmogorov Kolmogorov-Arnold-Moser (KAM) Theorem)
Paul Erdős & Alfréd Rényi (Random Graph Model/ Evolution of Random Graphs)
Thomas Schelling (Micro Motives/ Macro Behavior)
John Maynard Smith (Evolutionary Biology)
Robert Axelrod (ABMs & Complexity of Cooperation)
Benoit Mandelbrot (Founder)
Tien Yien Li (Founder)
James Yorke (Founder)
Otto Rössler (Attractors/Chaotic Fractals)
Edward Lorenz (Lorenz Attractor/ Butterfly Effect)
Mitchell Feigenbaum (Chaos Constant)
Lotfi Zadeh (Founder)
Bart Kosko (Fuzzy Logic)
John Doyle (Control and Dynamical Systems)
Jean Carlson (Complexity & Robustness)
Hiroaki Kitano (biological robustness)
James Crutchfield (Computational Mechanics/ Nonlinear Dynamics)
Peter M.A. Sloot (Information Processing/ multi-scale Modeling/ Computational Science)
Yaneer Bar-Yam (Systems Dynamics)
Stephanie Forrest (Computational Immunology Biological Modeling)
Per Lötstedt (Computation/ multi-scale modeling)
Alfons Hoekstra (Multiscale modeling and computing)
Dynamical Systems Theory
Graph Theory
Evolutionary Game Theory
Fractal Geometry
Chaos Theory
Nonlinear Systems
Fuzzy Logic
Robustness/ Control
Physics of Complex Systems
Hierachy in Complex Systems
Stephen Smale (Smale Horseshoe)
Chai Wah Wu (Graph Dynamical Systems)
Howard Odum (Ecological Systems Theory)
Lynn Margulis (Symbiogenesis Gaia Hypothesis)
Arne Næss (Deep Ecology)
James Lovelock (Gaia Hypothesis)
James Grier Miller (living systems theory)
Juval Portugali (Spatial/Urban Planning)
Alfred W. Hubler (Dynamics of Open Dissipative Systems)
Doyne Farmer (Dynamical Systems/ Economic complexity)
Göktuğ Morçöl (Public Admin/ Public Policy)
Michael Batty (Spatial/Urban Planning)
Peter Allen (Management Studies)
Andrzej Nowak (Dynamical Social Psychology)
Denny Borsboom (network theory mental illness)
Robin Vallacher (Dynamic Social Psychology)
Angélique Cramer (network theory mental illness)
Robert May (Population Dynamics)
Carlos Castillo-Chavez (Computational Biology/ Multi-level Modeling)
Yamir Moreno (Physics of Complex Systems)
Susan Stepney (Nonstandard Computation/ Bio-inspired Algorithms/ ABMs)
Roland Bouffanais (Engineering Complex Systems)
Juniper Lovato (Santa Fe Institute Complexity Education)
Matthijs Koopmans (Educational Leadership Psychological Complexity)
Brent Davis (Complexity in Education)
Frances Griffiths (Complexity in Health)
Yorghos Apostolopoulos (Population Health)
George Kaplan (Community Health)
Ludwig von Bertalanffy (Systems Theory Systems Biology)
Roger Barker (environmental psychology)
Bradford Keeney (Cybernetics, creativity, systems therapy)
Donella Meadows (globalization)
Alexander Bogdanov (Tektology/ Founder Systems Thinking)
Margaret Mead (Anthropology/ 2nd Order Cybernetics)
Systems Theory
Psychology Systems Theory
Ecological Systems Theory
Complex Living Systems
Complexity in Management & Planning
Complexity and Psychology
Systems Biology
Computational Biology/ Chemistry
biosystems engineering
Education
Healthcare
Public Health
Eshel Ben-Jacob (Self-Organization/ Bacterial sociality)
Ralph Stacey (Complexity & Management)
Mary Lee Rhodes (Public Administration/ Public Policy)
Han van der Maas (Computational Psychology)
Adele Hayes (change in therapy)
Jessica Flack (Computational Evolution)
Uri Alon (Network Motifs/Gene Expression)
Pier Luigi Luisi (Synthetic Life)
Caterina A. M. La Porta (Biosystems & Complexity)
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Kristen Hassmiller Lich (Operations research public health)
Kenneth Boulding (economics, ecology)
Kurt Lewin (Field Theory/ Social Psychology)
Fritjof Capra (web of life)
Jennifer Dunne (Ecology & Complexity/ Global Sustainability)
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Wertheimer, Koffka & Köhler (Gestalt Psychology)
J. J. Gibson and E. J. Gibson (Ecological Psychology)
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Francisco Varela (Cognitive Science)
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Nigel Thrift (Place & Time)
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Ana V. Diez Roux (Public Health)
Buckminster Fuller (Synergetics)
Warren Weaver (Complexity; Machine Translation)
Steven Strogatz (Dynamics/Small World)
Barry Wellman (Internet, INSNN)
Manuel Castells (Global Network Society)
Sylvia Walby (Gender/Inequality/ Globalization)
David Snowden (Organizations & Applied Complexity)
Alexandra Penn (Participatory Systems Mapping/ Environment)
Mark Granovetter (Strength of Weak Ties)
Complex Systems Theory
Self-Organization
Autopoiesis
Complex Adaptive Systems
Synergetics
Emergence
Swarm Behavior
Systems Dynamics/ Evolution
Scaling Hierarchies Boundaries
Resilience
Network Science
Complexity and Globalisation
Spatial/ Geographical Complexity
Intersectionality
Applied Complexity
Liz Varga (Engineering Resilient Complex Systems)
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Mirta Galesic (Human Social Dynamics)
Carl Folke (Coupled Ecosystems)
Roberta Sinatra (Networks & Data Science)
David O'Sullivan (GIS, geography & Complexity)
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Jac Vennix (Group Model Building)
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Per Bak (Self-Organized Criticality)
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Luis M. A. Bettencourt (Cities & Urbanization)
Duncan Watts (Small Worlds)
Réka Albert (scale-free networks)
Albert-Lazlo Barabasi (Scale-free networks)
Céline Rozenblat (Urban Complexity Networks/)
Ilya Prigogine (Dissipative Structure, time, matter)
Hermann Haken (Self-Organization and Synergetics)
Niklas Luhmann (Sociology)
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Cybernetics
2nd Order Cybernetics
Systems Science
Social Systems Theory
Socio-Cybernetics
Philosophy of Complexity
Economic Complexity
E-Science
BIG DATA Data Science
Digital Social Science
Visual Complexity
Complexity Political Science
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Michael Wooldridge (Editor, AAMAS)
Artificial Intelligence
Cognitive Science
Semiotics Linguistics
Cellular Automata
Connectionism
Computational Complexity Theory
Genetic Algorithms
Artificial Life
Agent Based Modeling
Robotics/ Multi-Agent Modeling
Data Mining
Computational Science
Computational Social Science
Case-Based Complexity
Qualitative Complexity
Interdisciplinary Methods
Warren McCulloch (AI Founder)
Evan Thompson (Embodied Mind)
Eleanor Rosch (Embodied Mind)
Frank Rosenblatt (Connectionism)
Hector Zenil (Algorithmic Complexity)
Christopher Langton (AI in computers)
Elizabeth E. Bruch (Quantitative Sociology)
Katia Sycara (Robotics/ Muti-agent Systems)
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The current literature is clear: there is an urgent need to apply a complex systems modelling approach to public health.

What is less clear is how to do this effectively.

Research and practice have shown mixed results, due to a series of dilemmas.

A short list includes:

a strong tendency to model public health issues instead of interrogating the development, implementation and evaluation of systems-level interventions

public health practitioners and funding organisations being biased toward simple, individual-level, short-term solutions based on clinical trials

modellers being tone deaf about the roadblocks to applying simulations to public health

the need to focus on stakeholder engagement

an overemphasis on computational models over qualitative methods

Fortunately, a small but growing global network of scholars are charting new territory. SSC being a great example!!!! ☺

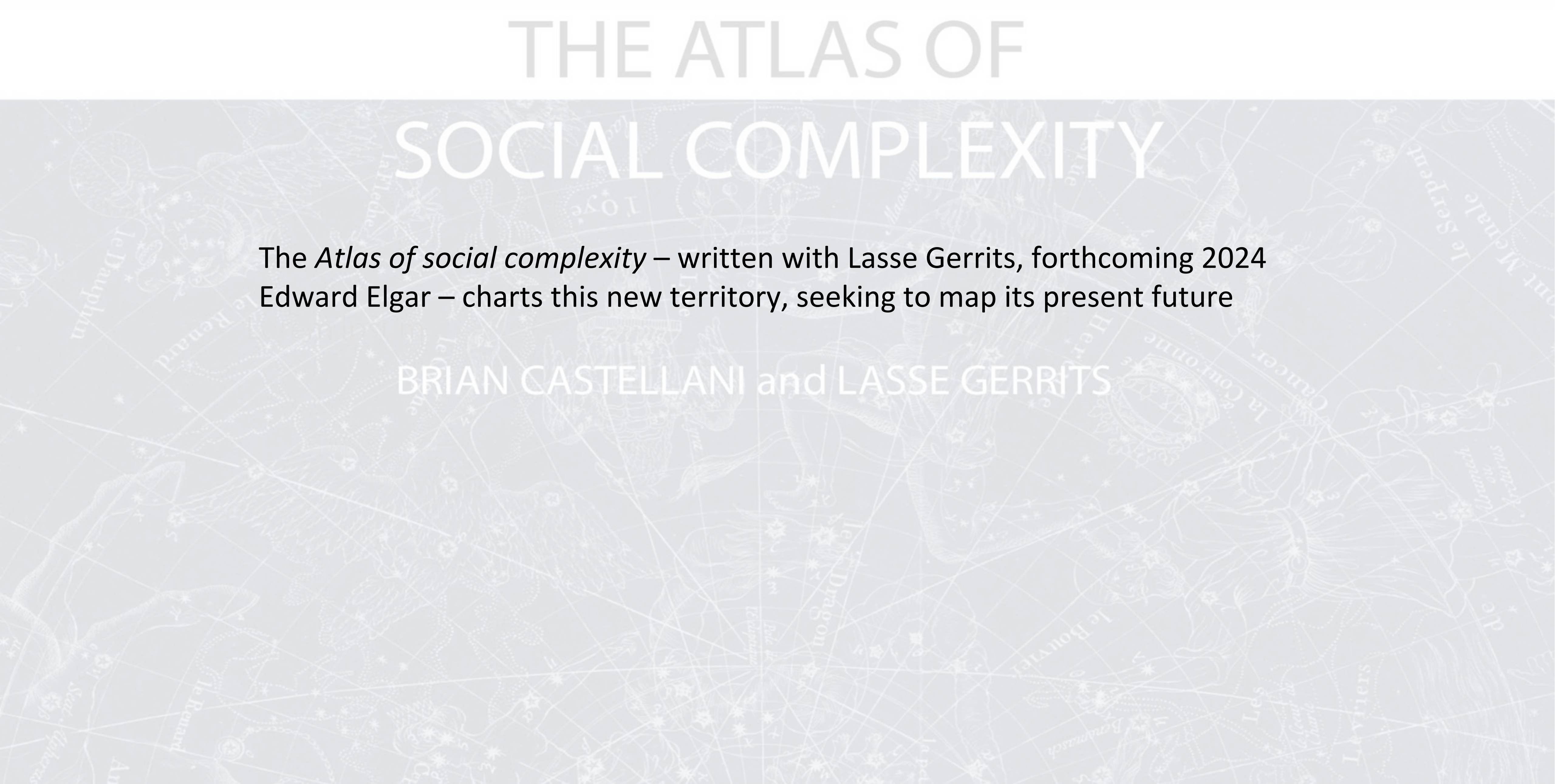
They are part of a fresh turn in complexity and modelling,
***the social science turn*.**

This turn (ideally) fosters a transdisciplinary, social complexity imagination that, in one way or another, addresses the field's current dilemmas to create new areas of disruptive and highly innovative social inquiry.

THE ATLAS OF SOCIAL COMPLEXITY

Lorem ipsum

BRIAN CASTELLANI and LASSE GERRITS



The *Atlas of social complexity* – written with Lasse Gerrits, forthcoming 2024 Edward Elgar – charts this new territory, seeking to map its present future

In terms of today’s talk, we will outline a set of ‘best practices’ for applying social complexity to public health modelling.

These include:

(1) challenging social physics and reductionism

(2) rethinking complex causality and system dynamics

(3) emphasising co-creation and context

(4) understanding real-world policy making

(5) modelling at multiple levels and with multiple models

(6) developing interdisciplinary methods and using qualitative data

(7) grounding models in rigorous social science

(8) accepting the limits of what modelling can do

Challenging social physics and reductionism

- The difference between computational science and computational social science
- We need to challenge the invasion of the physicists
- We need to challenge the naturalization of social systems
- All complex systems are not the same
  - Power,
  - psychology of complex systems
  - Irrationality
- General complexity versus restricted complexity – Edgar Morin

Rethinking complex causality and system dynamics

- Embracing a *configurational approach* to causality
  - moves research away from searching for the additive or net effect of some set of causal conditions (i.e.., factors, events, etc),
  - Exploring the multiple ways that different configurations of causal conditions may combined to produce a given outcome.
  - Pushes the researcher to engage in **four distinct ways of thinking** about complex social causality that are, in combination, theoretically innovative.

COMPLEX-IT 1.0.1 Beta - exploring complex data from a case-based perspective

Build Your Model

1. Build database and import your cases

2. Cluster your cases

Confirm & Explore Your Model

3. Use AI to confirm your cluster solution

4. Compare and visualize your results

Run Scenario Simulations

5. Simulate your scenarios, policies, and interventions

Run Data-forecasting/classification

6. Use AI to predict the cluster membership of new cases

Systems Mapping Tab

7. Using Sytems Mapping To Explore Cluster Variables

Export Your Results

8. Generate your report

Help

STEP 2: CLUSTER YOUR CASES USING K-MEANS

Here we will use k-means (a clustering algorithm) to group your cases into self-similar 'clusters'

For TUTORIALS on clustering your data in COMPLEX-IT CLICK HERE

For a basic introduction to k-means, See CLICK HERE

STEP 1: HYPOTHESIZE YOUR CLUSTER SOLUTION

1. **To begin, how many clusters do you think are in your database?**
2. **What is your hypothesis based on -- the literature, a guess, expertise, experience, a hunch?**
3. **How would you describe or name these different clusters?**
4. **How do you think your case-based profile of variables account for these different clusters?**

STEP 2: RUN THE K-MEANS

1. **Run your k-means several times to see if you can improve the Pseudo F**
2. **How strong is the Pseudo F for your solution?**
3. **Looking at the Silhouette, how well are the cases distributed for each cluster?**
4. **Should you re-run k-means to look for more or less clsuters?**
5. **SOME DEFINITIONS: The Pseudo F indicates the quality of the overall solution; the larger the number, the better the fit.**
6. **The Silhouette displays how well each case fits within its respective cluster; where a score of 1 is a perfect fit.**
7. **NOTE: The K-means solution and related statistics are found in the GENERATE REPORT TAB.**

Select display options.

- [x] Silhouette?
- [x] Pseudo F?

Select the number of clusters

4

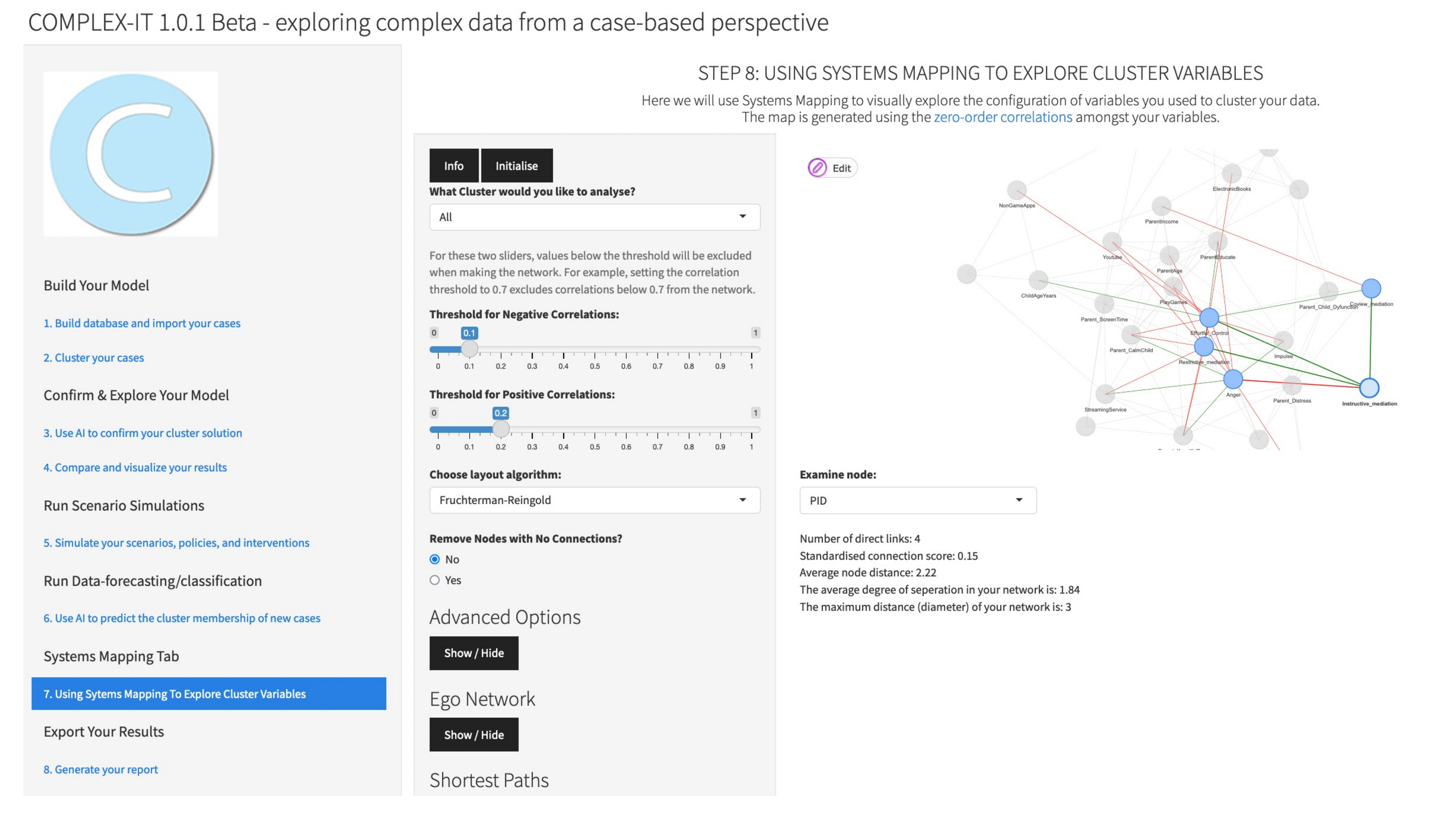
Do you want to set a seed for reproducible results?

- ( ) Yes
- (•) No

Get Clusters

Kmeans Cluster Centroids

Cluster	Size	PID	MEAN_SCORE	Parent_ScreenTime	Parent_Distress	Parent_Child_Dyfunction	Effortful_Control	Anger	Impulse	Instructive_mediation	Restrictive_mediation
Cluster 1	35	398.343	2.311	6.119	29.2	17.714	4.604	4.362	4.683	3.079	3.263
Cluster 2	42	178.19	2.449	6.804	26.167	18.571	4.714	4.34	4.448	3.027	3.16


COMPLEX-IT 1.0.1 Beta - exploring complex data from a case-based perspective
Build Your Model
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Run Data-forecasting/classification
6. Use AI to predict the cluster membership of new cases
Systems Mapping Tab
7. Using Sytems Mapping To Explore Cluster Variables
Export Your Results
8. Generate your report
STEP 8: USING SYSTEMS MAPPING TO EXPLORE CLUSTER VARIABLES
Here we will use Systems Mapping to visually explore the configuration of variables you used to cluster your data.
The map is generated using the zero-order correlations amongst your variables.
Info
Initialise
What Cluster would you like to analyse?
All
For these two sliders, values below the threshold will be excluded when making the network. For example, setting the correlation threshold to 0.7 excludes correlations below 0.7 from the network.
Threshold for Negative Correlations:
0.1
Threshold for Positive Correlations:
0.2
Choose layout algorithm:
Fruchterman-Reingold
Remove Nodes with No Connections?
No
Yes
Advanced Options
Show / Hide
Ego Network
Show / Hide
Shortest Paths
Edit
NonGameApps
ElectronicBooks
ParentIncome
Youtube
ParentEducate
ParentAge
ChildAgeYears
PlayGames
Parent_ScreenTime
Effortful_Control
Parent_Child_Dyfunction
Coview_mediation
Parent_CalmChild
Restrictive_mediation
Impulse
Anger
Parent_Distress
StreamingService
Instructive_mediation
Examine node:
PID
Number of direct links: 4
Standardised connection score: 0.15
Average node distance: 2.22
The average degree of seperation in your network is: 1.84
The maximum distance (diameter) of your network is: 3

Rethinking complex causality and system dynamics

Causal asymmetry: the idea that the configuration of causal conditions that lead to some outcome may be very different from the configuration of conditions that leads to the absence of that outcome.

Rethinking complex causality and system dynamics

Equifinality: the idea that different configurations of causal conditions can lead to the same outcome.

Rethinking complex causality and system dynamics

Multifinality: here we have the opposite idea: that similar configurations of causal conditions can lead to different outcomes; or what is also known as counterfactuals.

Rethinking complex causality and system dynamics

Conjunctural causation: the idea that a single condition impacts an outcome through its qualitative causal linkages with the other conditions in a configuration.

How different forms or types of interventions cancel out, work against or assist and improve (co-benefits, for example) other interventions.

Emphasising co-creation and context

- Interrogating the development, implementation and evaluation of systems-level interventions

- Stakeholder engagement and co-creation.
  - But it is not always and everywhere necessary.

- Context, context, context!!!!!

Understanding real-world policy making

- What is politically or policy-wise feasible?
- Who uses models anyway?
- ***And yet, some models are taking over***
  - ***Chatbot, AI, etc.***
  - ***Hayles and human machine assemblages – smart machines!***
- What type of evidence is necessary to support decision making?
  - Modelling versus clinical trials?
- How much evidence is needed to support decision making?

Understanding real-world policy making

- What happens when your model goes against or undermines decision making?
- Which politicians, civil servants or policy makers are you working with and who are in opposition to them?
- What are their models?

Leverage Points:
Places to Intervene in a System

by Donella H. Meadows

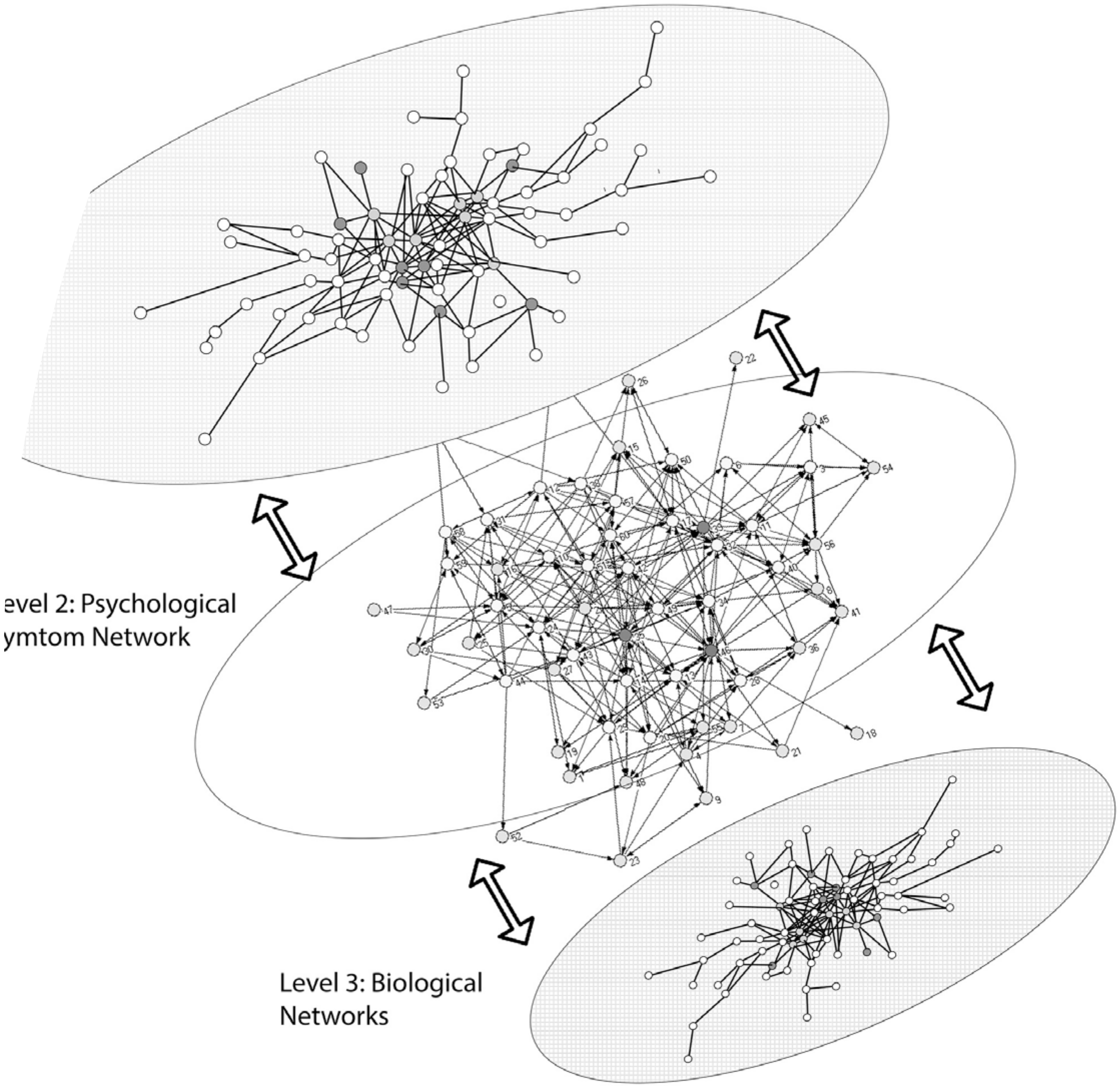
PLACES TO INTERVENE IN A SYSTEM

(in increasing order of effectiveness)

12. Constants, parameters, numbers (such as subsidies, taxes, standards).
11. The sizes of buffers and other stabilizing stocks, relative to their flows.
10. The structure of material stocks and flows (such as transport networks, population age structures).
9. The lengths of delays, relative to the rate of system change.
8. The strength of negative feedback loops, relative to the impacts they are trying to correct against.
7. The gain around driving positive feedback loops.
6. The structure of information flows (who does and does not have access to information).
5. The rules of the system (such as incentives, punishments, constraints).
4. The power to add, change, evolve, or self-organize system structure.
3. The goals of the system.
2. The mindset or paradigm out of which the system — its goals, structure, rules, delays, parameters — arises.
1. The power to transcend paradigms.

Modelling at multiple levels and with multiple models

- We need multiple models
- We need them at multiple levels of scale



Coronavirus: why we need local models to successfully exit lockdown

Published: May 18, 2020 10.18am BST

from www.shutterstock.com

It's fair to say the world has never been more aware of the importance of mathematical and statistical modelling as it is today.

National models for the COVID-19 epidemic, such as the one produced by Imperial College, in the UK have been at the forefront of public health decisions. This is mainly because they

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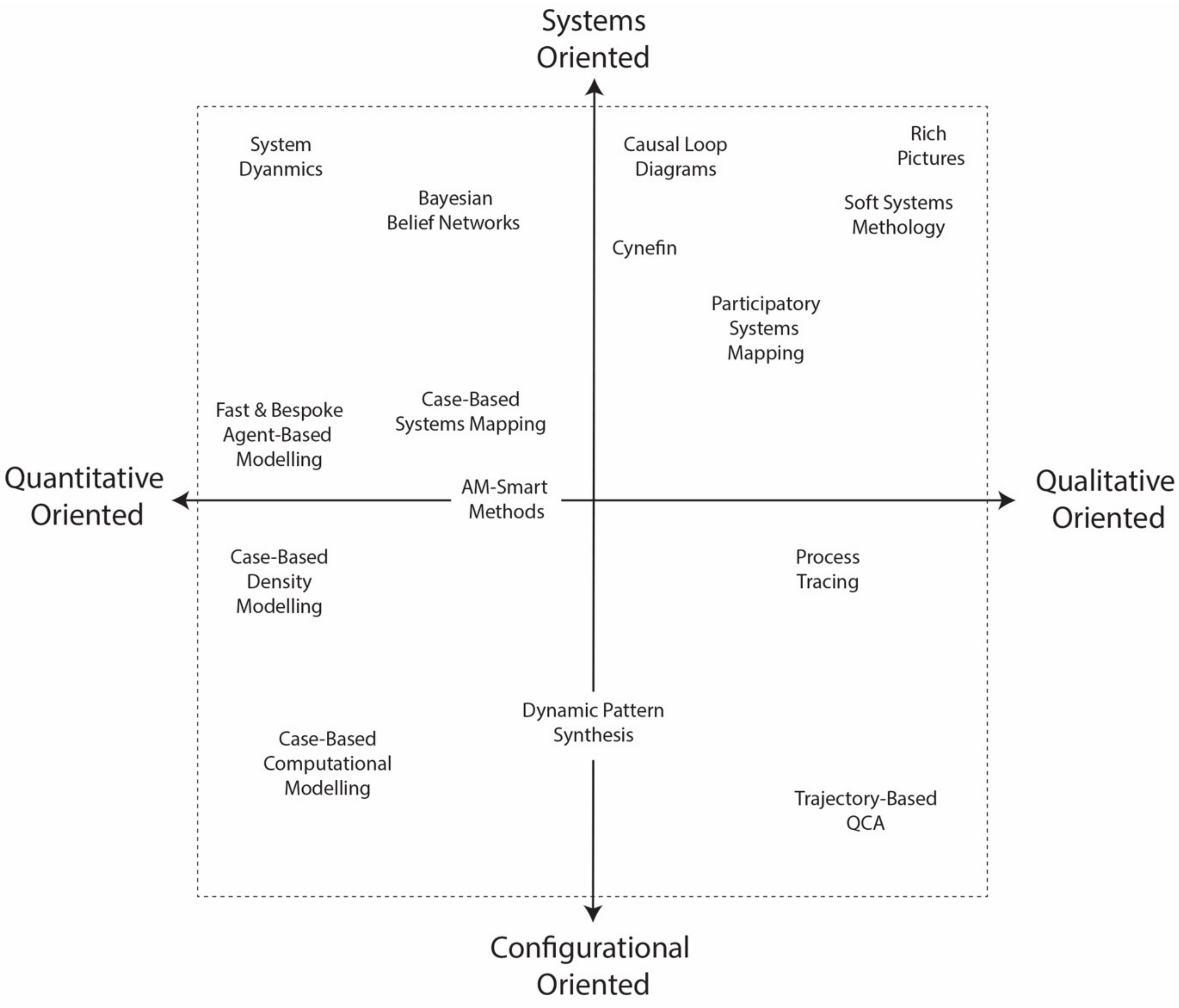
Developing interdisciplinary methods and using qualitative data

- Better positioning simulation within a larger suite of methods
- Example: systems mapping to system dynamics to agent-based model


Systems Oriented
Quantitative Oriented
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Configurational Oriented
System Dyanmics
Bayesian Belief Networks
Causal Loop Diagrams
Rich Pictures
Soft Systems Methology
Cynefin
Participatory Systems Mapping
Fast & Bespoke Agent-Based Modelling
Case-Based Systems Mapping
AM-Smart Methods
Case-Based Density Modelling
Process Tracing
Dynamic Pattern Synthesis
Case-Based Computational Modelling
Trajectory-Based QCA

GETTING AWAY FROM NUMBERS: USING QUALITATIVE OBSERVATION FOR AGENT-BASED MODELLING

LU YANG* and NIGEL GILBERT†

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Received
Revised

Although in many social sciences there is a radical division between studies based on quantitative (e.g. statistical) and qualitative (e.g. ethnographic) methodologies and their associated epistemological commitments, agent-based simulation fits into neither camp, and should be capable of modelling both quantitative and qualitative data. Nevertheless, most agent-based models (ABMs) are founded on quantitative data. This paper explores some of the methodological and practical problems involved in basing an ABM on participant observation and proposes some advice for modellers.

Keywords: Agent-based models; qualitative data; ethnography.

The right question isn't: Does the number mean anything? The right question is: Does the number correspond to a difference that makes a difference in the kind of world being modelled.[a]

Complex Dynamic Interactions: Synergies between ABM and QCA 2022

19 - 22 April 2022

Venue: Lorentz Center@**Snellius**

If you are invited or already registered for this workshop, you have received login details by email.

Agent-based modeling (ABM) as a methodology can easily integrate information on causality from various sources of knowledge, but building causal mechanisms into representing complex adaptive systems requires a heavy load of theoretical and empirical information.

Read more...

Program

Participants

Workshop files

Scientific organizers:

Timo Szczepanska, University of Tromsø

Patrycja Antosz, NORCE Norwegian Research Centre AS

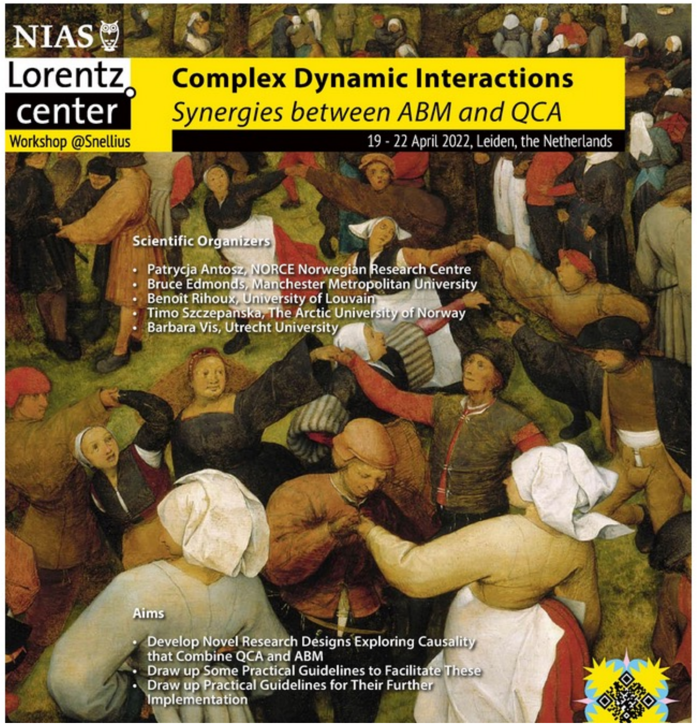
Bruce Edmonds, Manchester Metropolitan University

Benoît Rihoux, University of Louvain, UCLouvain

Barbara Vis, Utrecht University

Register

Log-in



Grounding models in rigorous social science

- Where is the social science theory?
- We need to learn more from the theories, empirical insights, and critical lens of the social sciences.
- We need models to give greater attention to relations of power, conflict, inequality.
- We need models to interrogate the institutional arrangements that commission models in the first place.

Accepting the limits of what modelling can do

- The *complexity turn* in social science originated out of scholars concerned with the limits of scientific inquiry.
- Postmodernism, feminism, philosophy and sociology of science, actor network theory and so forth.
- Are many of the concerns we have about modelling potentially really about the limits of what we can know and do?

- Complex realism: the world is ontologically complex. All models are undermined by their evidence.