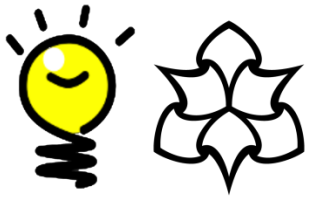
Manchester Metropolitan University

# *Strongly Empirical Modelling*

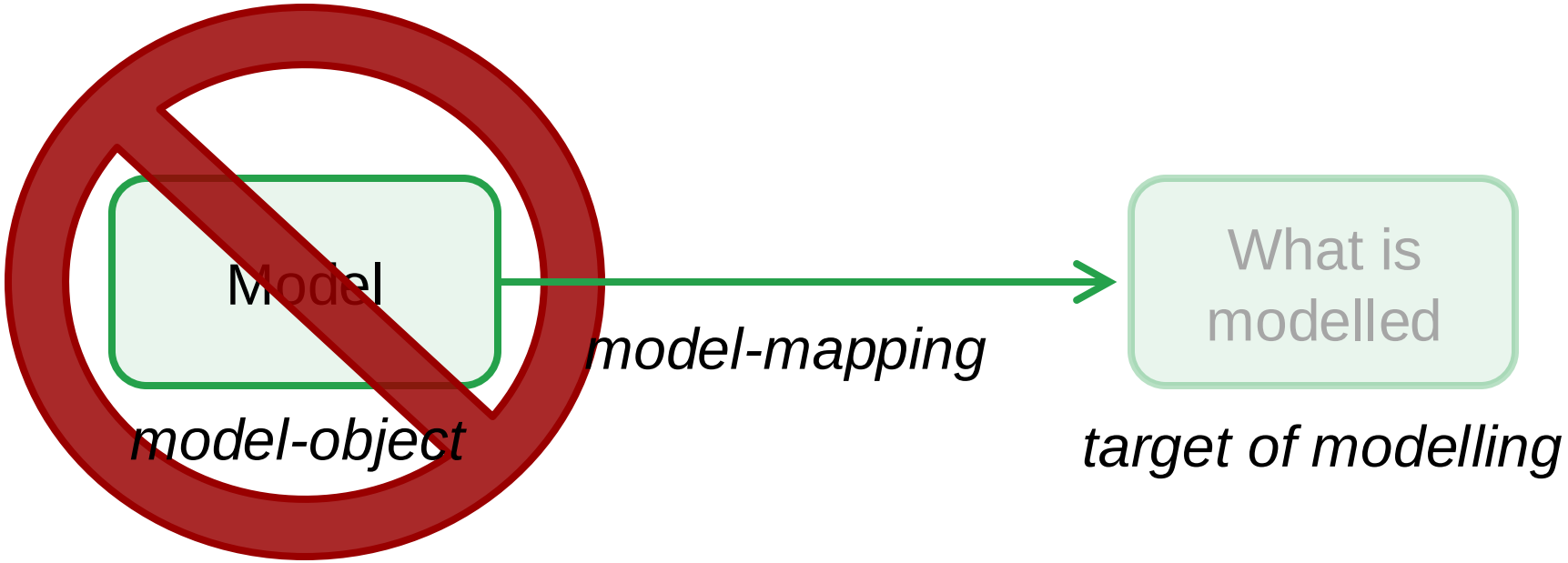
Bruce Edmonds, *Centre for Policy Modelling*
Dino Carpentras, *ETH Zurich*
Edmund Chattoe-Brown, *Uni. of Leicester*



Part 1

# The main argument

# A Model is *not* a Thing

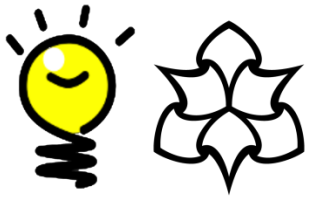



A model is a thing ***plus*** a mapping
(to what it models)

For example: *a random chunk of code or set of equations is* ***not*** *a model because it does not relate to anything*

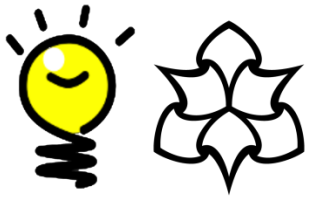
Wartovsky 1979

# the Emphasis in Social Simulation



- The emphasis of many modelling papers is on the ***thing*** – the model-object
  - Its: specification, structures, processes, properties, outcomes etc.
  - It is the bit we like to mess with
- Much less on the model-mapping – usually this is not closely defined, indeed, sometimes there is only vague motivation or is only implicit in the language we use (e.g. variable names)
- This paper paper looks at the mapping

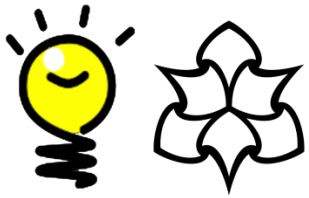
# Can you imagine…



…a physics where there is theory and models but only a hand-waving connection to the observable world (e.g. the gas laws but nobody had worked out how to measure temperature or volume reliably)? **No!**

The ***hard*** part of modelling is not making an entity with the right formal properties…
…but finding how and when to reliably map to what we observe

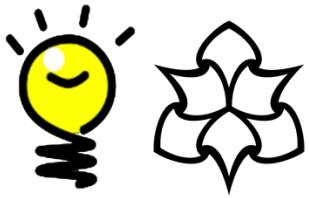
# Empirical Groundedness



A model is empirically grounded if and only if all its assumptions, structures, underlying theories, outcomes etc. either:

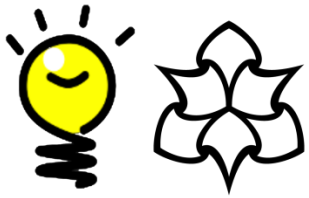
- Map to a set of data in a well-defined manner (which relates to the purpose of the model),
- Are uncontroversial – that is, it is not contested or seriously doubted by other researchers and could easily be empirically shown (e.g. that cars tend to drive on roads),
- Are themselves empirically grounded (using the same definition).

# Notes on this definition



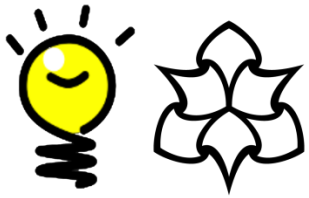
- This is a *recursive* definition, a model may rely on another model, theory, measurement etc. that may rely upon… etc. but you get to an end which is some data
- It does rely upon the judgement of modellers, but the result of chasing down this chain is that then *there is a clear process by which these judgements could themselves be empirically investigated*

# *Theoretical* **vs** *Empirical* **Modelling**



- A *theoretical model* is not empirically grounded but maps to ideas
  - It can be used to: illustrate an idea, explore theoretical properties, be a way of thinking about stuff
- An *empirical model* is empirically grounded, mapping (ultimately) to empirical data
  - It can be used to: support complex explanations, predict what may happen or simply act as a description of the observed

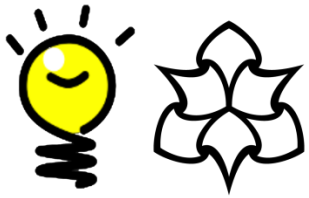
# The weaknesses of *broad-sweep* (or 'high') social theory



- *Vagueness* – lots of ill-defined aspects
- *Lack of clarity* in terms of its empirical support
- *Undefined scope* – when does it apply?
- *Context Conflation* – munges contexts together
- *Effect weakness* – only explains a bit of it
- *Suggestability* – a nice story
- Only *indirect mapping* to the observed (via ideas, theoretical objects etc.)
- *Selected for non-scientific reasons* (e.g. simplicity)

Antosz & al. 2023; Edmonds 2010

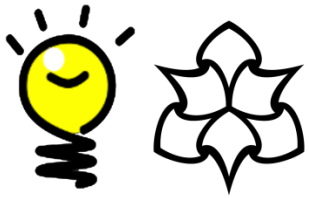
# So if not starting with *broad-sweep* social theory, then what?



Instead of an *impression* of progress – full of promise that is never empirically realised…

1. Precise models (e.g. simulations) that force assumptions to be explicit…
2. …*plus* a precise description of how elements of the model relate to empirical data
3. Compared to others to see which supports the best explanations in which situations
4. Gradual replacement of assumptions and theoretical bases with empirically grounded
5. With *later* generalisation if and when commonalities are observed

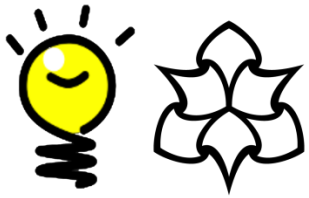
Edmonds & Moss 2005; Edmonds & al. 2023;



Part 2

# Some aspects of empirical modelling

# Modelling is not simple…



Models can be….

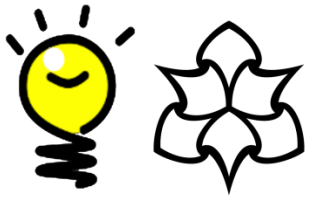
- for lots of different purposes
- related to empirical bases in different ways
- compared to other models in different ways
- etc.

There is not a "*one size fits all*" account but this does not stop us being rigorous

What follows is a brief discussion of some of these different aspects/dimensions (see paper for more)

Edmonds & al. 2019

# Mapping to specification, parameters or outcomes



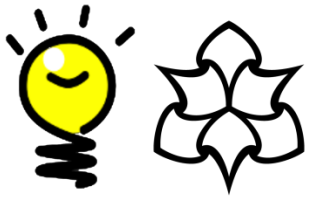
In…

1. Specification – aspects of the specification are mapped to what suggested them
2. Calibration – adjusting the input or parameters so a model fits some data
3. Validation – a post-hoc, independent check, comparing the outcomes to data

Or a combination of these

Banisch & Shamon 2024; Moss & Edmonds 2005

# Different kinds of precision

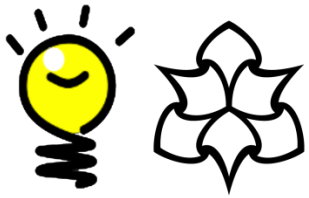


- Point precision relating to a measurement
  - but measurement noise etc.
- Distributional properties
- Broad qualitative patterns
- Processual accounts
- Structures (e.g. networks)
- etc.

All can be made more rigorous

Thorngate & Edmonds 2013; Abbas et al. 2013

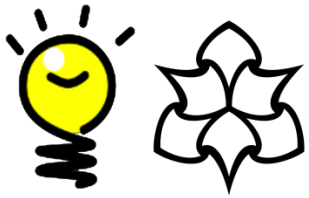
# Single vs. Multiple Dimensions



- Classically the aim of a model is to fit a single explained variable to data
- But a one-dimensional might not be enough to validate a simulation (it allows too much room for tuning parameters to get a fit)
- It is much stronger if many dimensions of a simulation can be simultaneously compared to empirical data
- Less precise fits (distributional/qualitative) can be traded for many dimensions

Grimm & al. 2005

# Comparing empirical strength of models



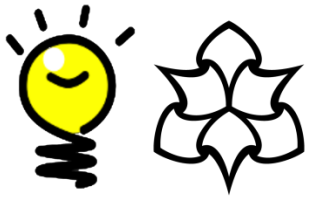
When comparing modelling one could look at:

1. How *much* of the variation/patterns observed in the outcome data is explained
2. How *certain* we can be that the match of model and data is not a matter of chance
3. How broad is the *scope* of the model, i.e. the set of circumstances where the model works well against the data

Instead of comparing models which explain little (but supposedly with a broad scope), maybe it would be better to look at narrowly scoped models that explain a lot

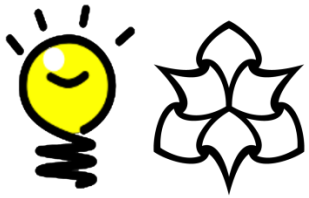
Moss & Edmonds 1998

# Difficulties of Empirical Modelling



- It is hard to do successfully
- Difficult to unearth hidden contextual assumptions
- Finding enough data of the right kind
- Modelling ill-defined or ill-measured phenomena
- Opening oneself up to criticism
- Time consuming
- Getting published

XXXXX



Part 3

# A suggestion and conclusions

# Technology Ready Levels

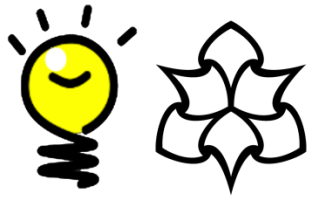

Héder 2017

Original TRLs invented by NASA in 1989 to avoid false impressions about readiness

But not ideally suited to simulation models

CloudWATCH2, 'A brief refresher on Technology Readiness Levels': https://www.cloudwatchhub.eu/exploitation/brief-refresher-technology-readiness- levels-trl [accessed 16 June 2022]

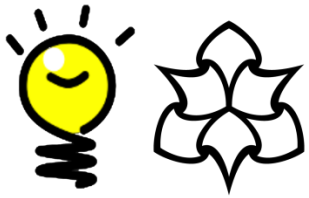
# Possible "*Modelling Ready Levels*"



| MRL | Criteria for Achievement |
|---|---|
| 1 | Concepts for an ABM described |
| 2 | Detailed specification for an ABM described |
| 3 | ABM is implemented, at least one run is shown |
| 4 | ABM assumptions etc. are all fully documented and the code is available |
| 5 | ABM is verified against specification and sensitivity analysis done |
| 6 | ABM is shown to be applicable to a situation, e.g. compared to some data/evidence or calibrated |
| 7 | ABM is sufficiently validated against evidence/data to show it is reliable for its declared purpose |
| 8 | ABM is shown to work for its intended use/situation, in practice |
| 9 | ABM is proven to work for the situation/problem described - repeatedly by users/stakeholders |

*This would aid clarity in calls for papers, grant proposals, model descriptions etc.*

# Conclusions



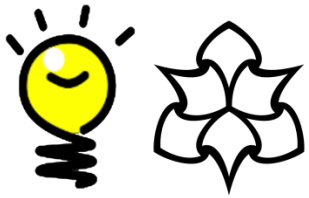
*If you have to change the model-mapping every time you "apply" the model-object to some new situation (or it is ill-defined) then you do not have strong empirical relevance*

We can do better than we are currently by…

1. thinking more about defining the mapping
2. taking care of the different ways to map
3. comparing models based on their mappings
4. being transparent about the level of empirical maturity of our modelling

Edmonds & al. 2023

# References in slides




Abbas, S.M.A., Alam S. J. and Edmonds, B. (2013) Validating Social Network Simulations, The 14th International Workshop on Multi-Agent-Based Simulation (MABS), Saint Paul, USA, 6-7th May, 2013.

Antosz, P., Birks, D., Edmonds, B., Heppenstall, A., Meyer, R. Polhill, J.G., O'Sulli-van, D. & Wijermans, N. (2023) What do you want theory for? - A pragmatic analysis of the roles of "theory" in agent-based modelling. *Environmental Modelling & Software*, 168, 105802. DOI: 10.1016/j.envsoft.2023.105802

Banisch, S. and Shamon, H. (2024) Validating Argument-Based Opinion Dynamics with Survey Experiments. *Journal of Artificial Societies and Social Simulation* 27(1), 17. http://jasss.soc.surrey.ac.uk/27/1/17.html.

Boero, R. and Squazzoni, F. (2005). Does Empirical Embeddedness Matter? Methodo-logical Issues on Agent-Based Models for Analytical Social Science. *Journal of Artificial Societies and Social Simulation*, 8(4), 6. https://www.jasss.org/8/4/6.html

Chattoe-Brown, E. (2014) Using Agent Based Modelling to Integrate Data on Attitude Change. *Sociological Research Online*, 19(1)16. http://www.socresonline.org.uk/19/1/16

Chattoe-Brown, E. (2023). Comparing Opinion Dynamics Models with Data: Opportunities and Challenges. *SocArXiv Papers*. https://doi.org/10.31235/osf.io/tnrbs

Edmonds, B. (2010) Bootstrapping Knowledge About Social Phenomena Using Simulation Models. *Journal of Artificial Societies and Social Simulation*, 13(1), 8. http://jasss.soc.surrey.ac.uk/13/1/8.html

Edmonds, B. & al. (2019) Different Modelling Purposes. *Journal of Artificial Societies and Social Simulation*, 22(3):6. http://jasss.soc.surrey.ac.uk/22/3/6.html

Edmonds, B. & al. (2023) Delusional Generality – how models can give a false impression of their applicability even when they lack any empirical foundation. *Review of Artificial Societies and Social Simulation*, 7 May 2024. https://rofasss.org/2024/05/06/delusional-generality

Edmonds, B. & Moss, S. (2005) From KISS to KIDS – an 'anti-simplistic' modelling approach. In Multi Agent Based Simulation 2004. Springer, *Lecture Notes in Artificial Intelligence*, 3415:130–144. http://cfpm.org/cpmrep132.html

Grimm, V. & al, (2005). Pattern-oriented modeling of agent-based complex systems: lessons from ecology. *Science*, 310(5750), 987-991.

Héder, M. (2017). From NASA to EU: the evolution of the TRL scale in Public Sector Innovation. *The Innovation Journal*, 22(2), 1-23.

Moss, S.J. and Edmonds, B. (1998). Modelling Economic Learning as Modelling, *Cybernetics and Systems*, 29, 5-37.

Moss, S. & Edmonds, B. (2005) Sociology and Simulation: - Statistical and Qualitative Cross-Validation, *American Journal of Sociology*, 110(4) 1095-1131.

Thorngate, W. & Edmonds, B. (2013) Measuring simulation-observation fit: An introduction to ordinal pattern analysis. *Journal of Artificial Societies and Social Simulation*, 16(2), 14. http://jasss.soc.surrey.ac.uk/16/2/4.html

Wartofsky, M. W. (1979). The Model Muddle: Proposals for an Immodest Realism. In *Models: Representation and the scientific understanding*. Dordrecht: Springer Netherlands, pp. 1-11.

# Thanks!

Manchester Metropolitan University

*These slides are at:* http://**cfpm.org/**slides
*as* "SSC2024 Strongly Empirical Modelling.pdf"
*(or use this QR code)*

Come to the conference sessions on "Strongly Empirical Modelling" or join the ESSA **Special Interest Group** on this subject by emailing *Dino Carpentras <dino.carpentras@gess.ethz.ch>*