A systematic procedure for developing multi-model architectures that support policy formulation across domains and scales: the case of school closures in the Netherlands

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Extended abstract:

Designing policies in complex health systems needs to account for the implications that a given policy may cause not only on the targeted domain but also on other and possibly related domains [17, 22]. For example, strong evidence demonstrates that the school closure policies introduced to curb the spread of COVID-19 (healthcare domain) had negative effects on the education of Dutch children, especially for those belonging to the most economically disadvantaged families (educational domain) [14, 10]. Further, policy implications can also affect multiple time (e.g. in the short and the long-term) [24, pp. 150-152] and organizational scales (e.g. central and decentral [16]). For example, the learning loss accrued during the pandemic due to school closure policies (short term) may produce a considerably negative effect on the economic opportunities today's children will have in the coming decades (long-term) [1].

Computational models can be effective tools for mapping such complex multi-domain and multiscale dynamics and provide policy support [13]. However, as exemplified by the case of the COVID-19 pandemic, the models developed for policy support typically focused on one domain e.g., epidemiology [2, 11]. Moreover, these models often investigated the short-term implications of policy interventions without considering their potential long-term impacts [2, 11], or overlooked central/de-central dynamics even when these were relevant [16, 9]. One potential reason for such design choices may be that using one model to capture multi-domain and multi-scale (long-term/short-term or central/de-central) dynamics can result in very detailed models that are computationally unfeasible or prone to high levels of uncertainty [20, 19]. To address these challenges, there is promise in using a combination of models (or multi-models) instead of one model [28, 25].

Multi-models are models composed of two or more sub-models capturing a phenomenon of interest at different scales and/or through different modeling paradigms. This modeling approach enables approximating a phenomenon of interest by functionally decomposing it into interacting sub-components each captured by a single model. A multi-modeling architecture (MMA) consists of the sub-models to be developed and their information exchange interactions. As such, given an MMA, a multi-model can be implemented by developing the sub-models delineated in the MMA.

In the literature, such a functional decomposition typically embraces two different perspectives, namely multiscale and multi-paradigm modeling. In multiscale modeling, the sub-models are designed to capture smaller portions of the original scales at which the dynamics of interest occur [6]. For example, different models could be developed for the short- and long-term implications of particular policies. These approximations can increase computational feasibility [4]. Multi-paradigm modeling focuses on capturing the sub-components of a system through adequate modeling paradigms e.g. by allocating very detailed paradigms (e.g. Agent-Based Models, ABMs) only where they are necessary and using less detailed paradigms (e.g. System Dynamics Models, SDMs) when such detail is not required [28, 23, 3, 5]. In sum, multiscale and multi-paradigm modeling provide greater flexibility compared to individual models in the allocation of model complexity where it is required, thus enabling researchers to seek a balance between model complexity and computational costs.

Developing MMAs that capture multi-domain and multiscale policy problems requires domain knowledge that spans several fields of expertise. As such, this knowledge may not be readily available to one modeler or even to a team of modelers. An effective approach for the development of these models can then be co-designing them with experts from different domains of interest [21, 27]. There is general consensus that developing models with experts enables not only to gather expertise from different fields but also to facilitate the generation of a shared problem understanding across multiple domains [26, 27]. In such a participatory process, a systematic and transparent approach is key at every step so that the experts can understand the model and contribute to its development [27]. This is particularly the case when transitioning from the development of qualitative conceptual models (e.g. Causal Loop Diagrams or CLDs) that are intuitive to understand, to quantitative computational models that are less easily understood by experts but enable them to fully explore the implications of the assumptions and decisions made [26].

The field of group model building provides conceptual modeling frameworks and procedures that enable to co-develop conceptual models with experts [26, 15] and translate them into *individual* computational models in a transparent and systematic manner [12, 18, 7]. This process requires clarity with respect to the domain knowledge that is required from experts to inform the development of a computational model. For example, [7] propose a conceptual modeling framework, namely the annotated Causal Loop Diagram (aCLD), that can capture the domain knowledge required from experts to build SDMs (e.g. mathematical expressions describing causal relationships). These authors then suggest a procedure for co-developing aCLDs with experts and translating them into SDMs in a transparent and systematic manner.

In the case of MMAs, the available literature has focused on the design of participatory modeling processes to facilitate mediation and mutual learning among different actors (including experts) to achieve a shared problem understanding in single domain and scale contexts [8]. However, clearly defined domain knowledge requirements and a procedure are missing that enable capturing the domain knowledge required to systematically and transparently develop MMAs with experts in multiscale and multi-domain contexts in a systematic and transparent manner.

In this article, we propose a systematic and transparent procedure to develop MMAs based on clearly-defined domain knowledge requirements derived from multi-paradigm and multi-scale modeling literature. To this end, we discuss seminal work in the field of multi-scale modeling and multi-paradigm modeling to identify (a) the key design choices involved in the development of MMAs and (b) the domain knowledge requirements to inform such design choices. These results inform the development of a procedure for developing MMAs. This procedure is then illustrated with the case of school closures in the Netherlands, by looking and their multiscale and multi-domain implications. Finally, we discuss the findings from the application and implications for the field of multi-model development for multi-domain and multi-scale policy support.

The MMA resulting from this application is composed of two sub-models, namely an ABM and an SDM. The ABM focuses on capturing the short-term implications of school closures in terms of epidemiological dynamics (susceptible, infected, recovered, and deaths). This model also captures the accumulation of learning loss due to the combined effect of (a) home-schooling resulting from school closures and (b) the economic situation of the children's families [1]. The ABM model runs each week for a total of two years. Once this simulation is completed, the final learning loss obtained from the ABM provides the initial condition for the SDM. This second model captures the (potential) long-term implications of the learning loss resulting from school closures on future job opportunities and on families' economic situation. This model will run every year for four decades. The next steps will include completing the development of the SDM and running simulations with the developed multi-model not only to assess the long-term implications of school closures on the economic situation of families but also to explore how such implications affect resilience to future crises.

The procedure for MMA development enabled us to systematically and transparently design an MMA illustrating the potential short- and long-term implications of school closures for the healthcare and education domains in the Netherlands. As such, the procedure shows promise in the transparent and systematic development of multi-models capturing multi-domain policy problems in public health and other sectors. Future research will focus on refining the procedure based on the case of school closures in the Netherlands and other cases. Additionally, while for this illustrative application the required domain knowledge was obtained from literature, future research will emphasize the design of participatory techniques that provide the means to effectively elicit the required domain knowledge from experts in multiple domains.

References

1. Agostinelli, F., Doepke, M., Sorrenti, G., Zilibotti, F.: When the great equalizer shuts down: Schools, peers, and parents in pandemic times. Journal of public economics **206**, 104574 (2022)
2. Badham, J., Barbrook-Johnson, P., Caiado, C., Castellani, B.: Justified stories with agent-based modelling for local covid-19 planning. Journal of Artificial Societies and Social Simulation **24**(1), 8 (2021)
3. Bonabeau, E.: Agent-based modeling: Methods and techniques for simulating human systems. Proceedings of the National Academy of Sciences **99**(suppl_3), 7280–7287 (2002). https://doi.org/10.1073/pnas.082080899, https://www.pnas.org/doi/abs/10.1073/pnas.082080899
4. Borgdorff, J., Ben Belgacem, M., Bona-Casas, C., Fazendeiro, L., Groen, D., Hoenen, O., Mizeranschi, A., Suter, J., Coster, D., Coveney, P., et al.: Performance of distributed multiscale simulations. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences **372**(2021), 20130407 (2014)
5. Borshchev, A., Filippov, A.: From system dynamics and discrete event to practical agent based modeling: reasons, techniques, tools. In: Proceedings of the 22nd international conference of the system dynamics society. vol. 22, pp. 25–29. Oxford, England (2004)
6. Chopard, B., Borgdorff, J., Hoekstra, A.G.: A framework for multi-scale modelling. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences **372**(2021), 20130378 (2014)
7. Crielaard, L., Uleman, J.F., Châtel, B.D., Epskamp, S., Sloot, P., Quax, R.: Refining the causal loop diagram: A tutorial for maximizing the contribution of domain expertise in computational system dynamics modeling. Psychological Methods (2022)
8. Cuppen, E., Nikolic, I., Kwakkel, J., Quist, J.: Participatory multi-modelling as the creation of a boundary object ecology: the case of future energy infrastructures in the rotterdam port industrial cluster. Sustainability Science **16**(3), 901–918 (2021)
9. Dekker, M.M., Coffeng, L.E., Pijpers, F.P., Panja, D., de Vlas, S.J.: Reducing societal impacts of sars-cov-2 interventions through subnational implementation. Elife **12**, e80819 (2023)
10. Engzell, P., Frey, A., Verhagen, M.D.: Learning loss due to school closures during the covid-19 pandemic. Proceedings of the National Academy of Sciences **118**(17), e2022376118 (2021)
11. Ferguson, N., Laydon, D., Nedjati Gilani, G., Imai, N., Ainslie, K., Baguelin, M., Bhatia, S., Boonyasiri, A., Cucunuba Perez, Z., Cuomo-Dannenburg, G., et al.: Report 9: Impact of non-pharmaceutical interventions (npis) to reduce covid19 mortality and healthcare demand (2020)
12. Ford, D.N., Sterman, J.D.: Expert knowledge elicitation to improve formal and mental models. System Dynamics Review: The Journal of the System Dynamics Society **14**(4), 309–340 (1998)
13. Gilbert, N., Ahrweiler, P., Barbrook-Johnson, P., Narasimhan, K.P., Wilkinson, H.: Computational modelling of public policy: Reflections on practice. Journal of Artificial Societies and Social Simulation **21**(1) (2018)

14. Haelermans, C., Jacobs, M., van der Velden, R., van Vugt, L., van Wetten, S.: Inequality in the effects of primary school closures due to the covid-19 pandemic: Evidence from the netherlands. AEA Papers and Proceedings **112**, 303–07 (May 2022). https://doi.org/10.1257/pandp.20221107, https://www.aeaweb.org/articles?id=10.1257/pandp.20221107
15. Hovmand, P.S., Andersen, D.F., Rouwette, E., Richardson, G.P., Rux, K., Calhoun, A.: Group model-building 'scripts' as a collaborative planning tool. Systems Research and Behavioral Science **29**(2), 179–193 (2012)
16. Janssen, M., Van der Voort, H.: Agile and adaptive governance in crisis response: Lessons from the covid-19 pandemic. International journal of information management **55**, 102180 (2020)
17. Klement, R.J.: Systems Thinking About SARS-CoV-2. Frontiers in Public Health **8**, 585229 (2020). https://doi.org/10.3389/fpubh.2020.585229
18. Mooy, R., Rouwette, E., de Valk, G., Vennix, J., Maas, A.: Quantification and evaluation issues in group model building: an application to human resource management transition (2001)
19. Puy, A., Beneventano, P., Levin, S.A., Lo Piano, S., Portaluri, T., Saltelli, A.: Models with higher effective dimensions tend to produce more uncertain estimates. Science Advances **8**(42), eabn9450 (2022)
20. Rahmandad, H., Sterman, J.: Heterogeneity and network structure in the dynamics of diffusion: Comparing agent-based and differential equation models. Management science **54**(5), 998–1014 (2008)
21. Rouwette, E.A., Vennix, J.A., Mullekom, T.v.: Group model building effectiveness: a review of assessment studies. System Dynamics Review: The Journal of the System Dynamics Society **18**(1), 5–45 (2002)
22. Sahin, O., Salim, H., Suprun, E., Russell Richards, MacAskill, S., Heilgeist, S., Rutherford, S., Stewart, R.A., Beal, C.D.: Developing a Preliminary Causal Loop Diagram for Understanding the Wicked Complexity of the COVID-19 Pandemic. Systems **8**(2), 20 (Jun 2020). https://doi.org/10.3390/systems8020020, https://www.mdpi.com/2079-8954/8/2/20, number: 2 Publisher: Multidisciplinary Digital Publishing Institute
23. Scholl, H.J.: Agent-based and system dynamics modeling: a call for cross study and joint research. In: Proceedings of the 34th annual Hawaii international conference on system sciences. pp. 8–pp. IEEE (2001)
24. Sterman, J.: Business dynamics (2000)
25. Vangheluwe, H., De Lara, J., Mosterman, P.J.: An introduction to multi-paradigm modelling and simulation. In: Proceedings of the AIS'2002 conference (AI, Simulation and Planning in High Autonomy Systems), Lisboa, Portugal. pp. 9–20 (2002)
26. Vennix, J.A.M.: Group Model Building: Facilitating Team Learning Using System Dynamics. Wiley (Aug 1996)
27. Voinov, A., Bousquet, F.: Modelling with stakeholders. Environmental modelling & software **25**(11), 1268–1281 (2010)
28. Zeigler, B.P., Ören, T.I.: Multifaceted, multiparadigm modeling perspectives: Tools for the 90's. In: Proceedings of the 18th conference on Winter simulation. pp. 708–712 (1986)