SIMULATING CHANGE: A SYSTEMATIC LITERATURE REVIEW OF AGENT-BASED MODELS FOR POLICY-MAKING

Michael Belfrage[a b], Fabian Lorig[a b], and Paul Davidsson[a b]

[a]Department of Computer Science and Media Technology, Malmö University, Sweden
[b]Internet of Things and People Research Center, Malmö University, Sweden
{michael.belfrage,fabian.lorig,paul.davidsson}@mau.se

ABSTRACT

Social phenomena emerge from agent-environment interactions, rendering many statistical models unsuitable. Agent-based Models (ABMs) offer a viable alternative for exploring policy implications. While recent crises like the COVID-19 pandemic may have increased ABM awareness, their use in policy-making has a long history. To better understand the potential challenges and opportunities of using ABMs to inform policy-making, we conducted a systematic literature review and identified 34 articles describing the use of ABMs involving policymakers. This review revealed that ABMs have been implemented to support policymakers across a range of policy areas, but also identified low levels of model traceability and formal communication. Moreover, the review showed that the model's purpose and type tend to influence how validation is performed. The review concludes that models that have undergone little validation and lack proper documentation, while being informally communicated, may hinder policymakers from effectively motivating their decision-making.

Keywords: agent-based modeling and simulation, policy-modeling, policy-making, policy support

1 INTRODUCTION

Agent-based Models (ABMs) are increasingly viewed as valuable tools for informing policy-making. See Figure 1 for the publication trend, where the data was collected from the Scopus database and includes publications between 1995 and 2022. Since social systems tend to be technically complex and are comprised of social agents that interact with each other and their environment, the instrumentalist approach using statistical models that assume independence falls short in explaining this dynamic interaction and the emergence of social phenomena [1]. Therefore, it is not surprising that research into methods, guidelines, and pitfalls for the use of ABMs in policy-making is steadily increasing [2, 3, 4, 5, 6]. Using ABMs to simulate policy interventions – which is sometimes referred to as policy modeling – allows the user to evaluate simulated policy experiments [2]. This presents a safe environment in which different policies, or combinations thereof, can be tested before implementation in the target system. This makes policy modeling a practice that facilitates evidence based policy-making, where scientific methods are integrated into political governance, aiming to formulate policy solutions best suited to address the problem at hand [4].

However, there are still several challenges that could impede the widespread adoption of the complex systems framework for policy analysis [7]. Agent-based modeling constitute a sandbox paradigm, considered relatively novel and rapidly evolving; thus, its full potential is yet to be realized [8]. The system design of ABMs, such as included and omitted parameters, depends on the model's purpose and the design choices of modelers. Therefore, any inferential claim of an ABM is specific to its purpose and the process it aims

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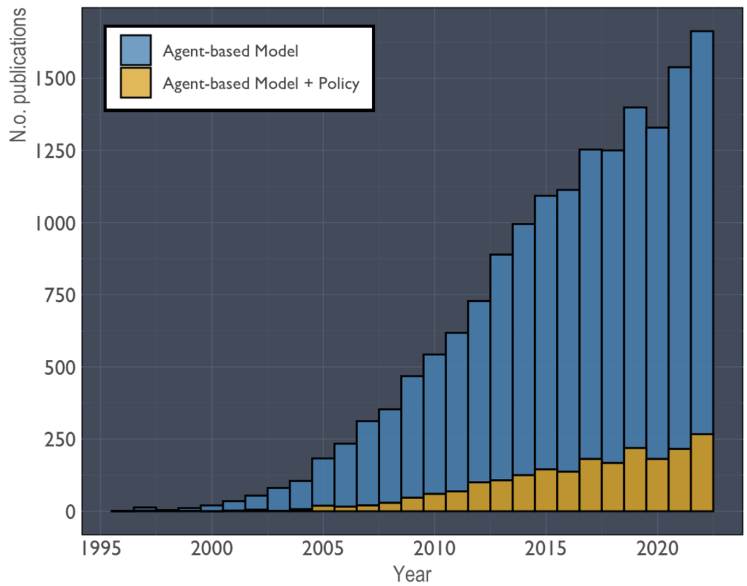

Figure 1: The publication trend according to the keywords in the legend.

to emulate through simulation [9]. As a consequence, the formalization and validation of ABMs become resource-intensive, demanding high levels of technical competence and domain expertise. To tackle these challenges, modelers frequently engage in symbiotic cooperation with stakeholders and domain experts throughout their projects. In design, this collaboration increases the diversity of ideas that are collected and integrated into a simulation model, allowing for better solutions to complex problems [10]. In application, such collaborations also expedites knowledge integration and serves to decentralize decision-making power [11]. However, when used in formal policy-making processes the documentation and traceability of models become crucial. This ensures that the rigor of policy models can be evaluated before application [12], allowing policymakers to justify their decisions [13].

ABMs have the potential to become invaluable tools for policy-making, elucidating system interactions and offering a suitable alternative when conducting policy pilots might be too expensive or impossible to perform [2]. However, for this potential to be realized, there is a need to establish best practices for the use of ABMs in policy-making. An important step in this direction is to investigate how policy-modeling has been conducted across various fields of application, involving stakeholders and policymakers, to learn from already completed projects. Accordingly, the purpose of this literature review is to consolidate knowledge from the scientific literature to identify opportunities and challenges facing the use of ABMs in policy-making. This is achieved by focusing on how collaborations are actualized, the common methodological practices, and how ABMs have been used to inform policymakers.

- What are the potential challenges and opportunities for using policy-modeling to inform policy-making?
  – In what policy areas and contexts has policy-modeling been used together with policymakers?
  – How were policy-modeling projects conducted together with policymakers and stakeholders?
  – Do model related factors contribute to the adoption of distinct validation strategies and the dissemination of information to policymakers?
  – What is the traceability of agent-based models used for policy-making?

2 SEARCH STRATEGY AND SELECTION CRITERIA

We conducted a systematic literature review to examine how policy models have been used together with policymakers. To this end, we developed a search strategy including four different components, which we applied to search for articles in the Scopus database. The four components of this search string focused on the type of model, the collaborative aspects of the project, the type of actors involved in the project, and the purpose of using the model to inform policy: `(TITLE-ABS-KEY (agent-based) OR TITLE-ABS-KEY (individual-based) OR TITLE-ABS-KEY (policy-model) OR TITLE-ABS-KEY (computational-model) AND TITLE-ABS-KEY (collaboration) OR TITLE-ABS-KEY (support) OR TITLE-ABS-KEY (participatory) OR TITLE-ABS-KEY (companion) AND TITLE-ABS-KEY (policymaker) OR TITLE-ABS-KEY (stakeholder) OR TITLE-ABS-KEY (decision-maker) AND TITLE-ABS-KEY (policy) OR TITLE-ABS-KEY (policies)) AND (LIMIT-TO (LANGUAGE , "English"))` The search string generated a list of 273 articles.

By screening titles and abstracts, we included 97 articles according to the inclusion criterion, which required that the research used ABMs. After considering the full text of the remaining 97 articles, we excluded 63 articles according to the exclusion criterion, meaning articles that did not involve policymakers. Some of these also contained multiple simulation applications, such as comprehensive project reports or other literature reviews, often lacking the necessary depth to be aligned with the aim of the current literature review, making the final sample (n=34). This search process is illustrated in Figure 2.

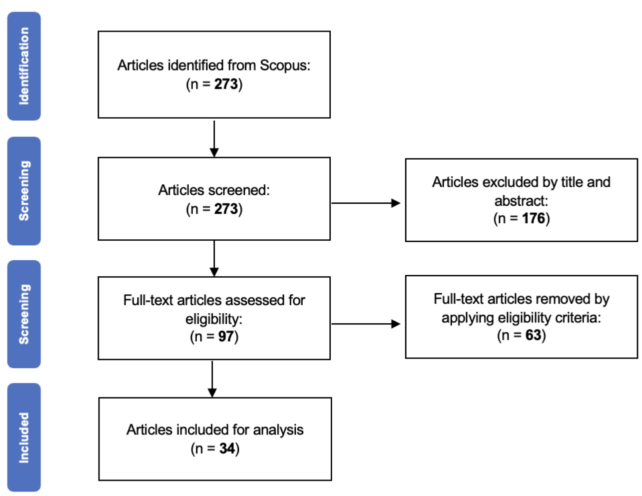

Figure 2: Flow chart depicting the search process.

The definition of stakeholders used by the world bank could be understood to include policymakers: *an individual, organization, or group that has something to gain or lose, either directly or indirectly, from the outcome of a policy reform* [14]. However, it is important to note that in our context, we make a distinction between policymakers — meaning the actors with direct influence over policy-making — and stakeholders that are affected by the outcome of a policy reform, based on our selection criteria. As a result, a potential risk associated with using this method is that the term "stakeholder" could inadvertently refer to policymakers, causing type-II errors and biasing our sample. The second challenge, which is commonly shared among all systematic reviews, lies in identifying relevant search terms. Our objective was to identify terms that denote ABMs and participatory projects involving policymakers. During this process, we also aimed to distinguish between the many articles that merely motivate the importance of their work for policy-making from those articles that have used their models to inform policy-making. This differentiation was crucial to reduce the number of exclusions and maintain a manageable article count. Consequently, the applied strategy aims to maximize relevance rather than providing an exhaustive search.

3 POLICY MODELS AND COLLABORATIONS

The 34 articles included, based on the previously defined inclusion and exclusion criteria, were published between the years 2000 and 2022. The software used to implement the policy models is broad in scope, ranging from general-purpose languages like C++ to more ABM-specific software like NetLogo or AnyLogic, as illustrated in Figure 3. A total of 26.5% did not declare the platform in which they implemented their model. The most commonly applied software includes NetLogo, Cormas, and AnyLogic.

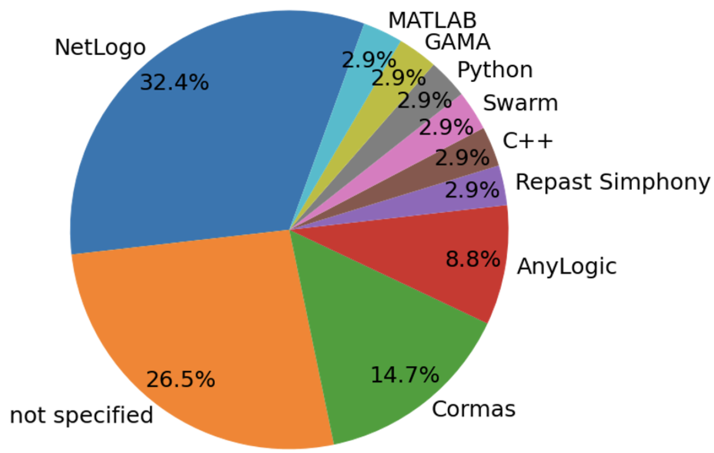

Figure 3: The software used to implement policy models.

The ABM tradition of using models for collective resource management problems in policy areas like land-use, agriculture, and water management is well represented. Additionally, there are several applications in logistics areas like transportation and urban freight, as well as economic modeling and disaster management. The distribution of the main policy areas these models focus on is presented in Figure 4. It is worth noting that there is considerable overlap between different policy areas. For example, while the primary focus of a model's output may be water management, agriculture, fisheries, or land-use, many applications in these areas explore climate change as a cause for these different effects [15, 16, 17]. There is also much technical similarity between applications in certain policy areas. Models for land-use and agriculture may share many technically similar factors, such as farmer-agents, objects and processes in-between models. Land-use policy may leverage ABMs to examine land-use transitions to pinpoint vulnerable areas [18, 19, 20]. On the other hand, agricultural policies may aim to incentivize the adoption of farming innovations [21, 22].

The complete list of included articles can be found in Table 1. ABMs have been applied to aid contentious negotiations and find acceptable solutions by balancing trade-offs between groups of stakeholders in scarce resource management problems [48, 24]. Other optimization problems involve the use of an ABM by NASA to evaluate airfare pricing strategies in the US air transportation system [35], and maritime shipping routes optimization to avoid pirate encounters [37]. Additionally, several models focused on counterfactual scenario analysis by testing different policy interventions. For example, the European Commission used an ABM to explore funding strategies in research and innovation policies [31], while in Austria an ABM is employed in the training of ambulance personnel for disaster management [38]. The sample also include three public health applications related to the SARS-CoV-2 virus, including the modeling of non-pharmaceutical interventions in the UK and Costa Rica [27, 26], and investigating patient flows in emergency departments [25].

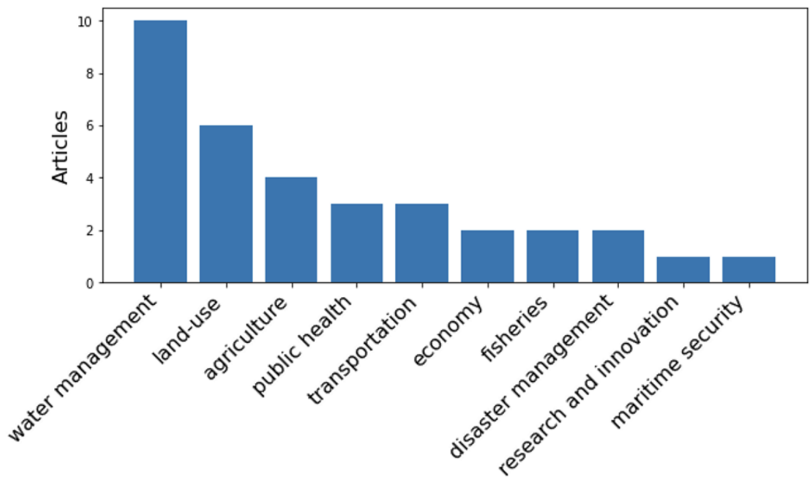

Figure 4: The distribution of policy areas in which the policy models are applied.

Participation refers to whether the project only included policymakers or whether stakeholders were also included in the process. In 59% of the articles, participants reported using a bottom-up approach, including both policymakers and stakeholders, and 41% of articles reported using a top-down approach. The agent-based simulation community has long used stakeholder participation as a strategy to both increase the value of models to practitioners and promote public involvement [49, 11]. However, certain policy models make promoting participation difficult, as it also depends on how the costs and benefits of the policies are distributed [50]. Within the 41% of articles employing a top-down approach, 78.6% also include stakeholders belonging to a diffuse group. This means that the costs and benefits of such policies cannot be attributable to any clearly delineated stakeholder group, making identification of suitable stakeholders a more challenging task. For example, with COVID-19 models in mind, anyone susceptible to virus could be viewed as a stakeholder, implying society at large. This is likely a reflection of the fact that policy-modeling is a tool for policy-making that addresses broad societal challenges.

Individual accounts in the current literature review suggest that participation in policy-modeling can be challenging. First, policy-modeling needs to be fast to be useful for policymakers, who often have limited time, making extensive participatory approaches less applicable [31]. Second, from a bottom-up perspective, going through stakeholders to policymakers, has previously resulted in modelers losing their primary policymaker contact, thereby preventing the application of the model [43]. This may indicate that not anchoring the project in its early stages within an institutional setting, where several policymakers are committed to the project, could potentially make follow-through more difficult. Lastly, in another bottom-up project, scientists reported concerns about their own role within the project. As the core researchers of the group planned activities that were perceived to steer policy outcomes toward their own interests and not necessarily that of their participants [32], this indicates a need to reflect on the role that scientists should fill in the policy-making context and the ethical implications different levels of involvement might have.

We also investigated which administrative level the different included policymakers belonged to; some projects also included policymakers from several levels. The observable trend is that the participation of policymakers tends to be more common at the local level (44.1%) and regional level (38.2%), while it occurs less frequently at the national level (20.1%) and supranational level (6%). According to the participatory simulation approach, earlier inclusion of stakeholders aids in bolstering model validity [51]. This is especially true in policy-modeling, since policymakers can be considered experts in the systems they govern. Therefore, we investigated at what stage policymakers were included. 35.3% reported including policymakers during the model design stage, another 35.3% included policymakers during the intervention

Table 1: List of all models included in this study.

Nr	Year	Location	Use-case	Model Type	Participation	Ref
1	2022	Indonesia	Evacuation strategies for volcanic eruptions	Deterministic	Bottom-Up	[23]
2	2022	Chile	Water management and resource negotiation	Stochastic	Bottom-Up	[24]
3	2022	Norway	Patient flows in emergency department (COVID-19)	Stochastic	Top-Down	[25]
4	2022	Costa Rica	Non-pharmaceutical interventions for disease prevention (COVID-19)	Stochastic	Top-Down	[26]
5	2021	England	Non-pharmaceutical interventions for disease prevention (COVID-19)	Stochastic	Top-Down	[27]
6	2021	Italy	Alp catchment consequences of climate change	Stochastic	Bottom-Up	[28]
7	2021	Thailand	Dam construction and equal utility distribution	Stochastic	Bottom-Up	[29]
8	2021	Madagascar	Food shortages and poverty	Stochastic	Bottom-Up	[20]
9	2020	Zimbabwe	Collective agricultural resource management	Stochastic	Bottom-Up	[30]
10	2019	EU	Maximizing research proposals from research institutions	Stochastic	Top-Down	[31]
11	2018	Ghana	River bank cultivation	Deterministic	Bottom-Up	[32]
12	2017	Alaska	Sustainable fishery practices	Stochastic	Top-Down	[16]
13	2017	Italy	Optimizing urban freight transport policies	Stochastic	Bottom-Up	[33]
14	2016	Vietnam	Climate change mitigation measures for land-use	Deterministic	Bottom-Up	[17]
15	2016	France	Adoption of organic farming practices	Stochastic	Bottom-Up	[21]
16	2015	Netherlands	Changing land-use patterns	Stochastic	Bottom-Up	[19]
17	2015	USA	Sustainable Urban Water Management	Deterministic	Top-Down	[34]
18	2015	Ethiopia	Adoption of agricultural practices	Deterministic	Top-Down	[22]
19	2014	USA	Optimizing airfare prizing strategies	Stochastic	Top-Down	[35]
20	2014	Senegal	Countermeasures for land degradation	Deterministic	Bottom-Up	[36]
21	2013	Indian Ocean	Counter-piracy strategies	Stochastic	Top-Down	[37]
22	2012	Austria	Training first-responders for disaster-responsive ambulance services	Stochastic	Top-Down	[38]
23	2012	Netherlands	Rural development strategies	Stochastic	Top-Down	[39]
24	2012	USA	Water reservoir consequences of urban development	Deterministic	Top-Down	[40]
25	2010	France	Sustainable forest management strategies	Deterministic	Bottom-Up	[41]
26	2010	Chile	Willingness-to-pay for irrigation water	Stochastic	Top-Down	[42]
27	2010	Thailand	Sustainable razor clam harvesting	Stochastic	Bottom-Up	[43]
28	2009	Indonesia	Food shortages and poverty	Stochastic	Top-Down	[44]
29	2008	Spain	Collective water management and resource negotiation of	Deterministic	Bottom-Up	[45]
30	2008	EU	Sustainable mobility system transitions	Deterministic	Top-Down	[46]
31	2006	Vietnam	Changing land-use patterns	Deterministic	Bottom-Up	[18]
32	2005	Spain	Optimizing water supply-and-demand policies	Stochastic	Top-Down	[47]
33	2002	Senegal	Land-use management and resource negotiation	Deterministic	Bottom-Up	[48]
34	2000	England	Water reservoir consequences of climate change	Stochastic	Top-Down	[15]

design stage, while 14.7% reported meeting policymakers after the modeling was done to present the results, and another 14.7% of the articles did not specify when policymakers were included.

We also investigated the various activities leveraged for data collection, which are later utilized in model design, calibration, and validation. In this review, 91.1% of collaborations with policymakers involved various types of meeting activities. Information from these meetings is often used to construct a conceptual model, design interventions, and validate model implementations. Furthermore, 29.4% of projects employ various forms of serious games to calibrate agent behavior. Similarly, interviews are also used for the same purpose. Another method used by 32.4% of all articles for data collection is surveys. We note that survey methodology could potentially be leveraged in policy-modeling applications with diffuse policy stakeholder groups allowing to consider public opinion and participation. One applied survey method involved collecting choice data, which was later used to estimate utility functions and preferences for calibrating agent behavior [19, 33].

A clear majority of collaborations involving policymakers use secondary data. Many articles report that policymakers and stakeholders provide secondary data, which is often complemented with public data from statistical agencies or other public administrations. However, there are also reports indicating several potential challenges related to data availability and accessibility from policymakers and stakeholders. For instance, the lack of appropriate and accessible data might necessitate additional data collection prolonging the project [41], make quantitative validation impossible [39], result in difficulties of parameter estimation [19], confound parameters [26], or require simplifying model assumptions [42, 25]. This suggests that a timely investigation of data availability and accessibility is crucial in policy-modeling projects.

4 VALIDATION STRATEGIES AND MODEL TRACEABILITY

In Figure 5, each line represents one policy model application, and is segmented by color indicating the cluster according to the four validation variables in the plot. The clusters in this visualization were produced using the k-medoids algorithm with the four model validation variables — quantitative validation, robustness checks, sensitivity analysis, and face-validation — as input data. This parallel coordinate plot allows for a fairly straightforward interpretation of each application, covering aspects such as the purpose and type of the model, model validation, and how the model information was shared with policymakers. One account also cautions that policymakers expected modelers to formulate findings as policy advice [31], potentially blurring the lines between the modelers' role as facilitators and active participants in the decision-making process [52].

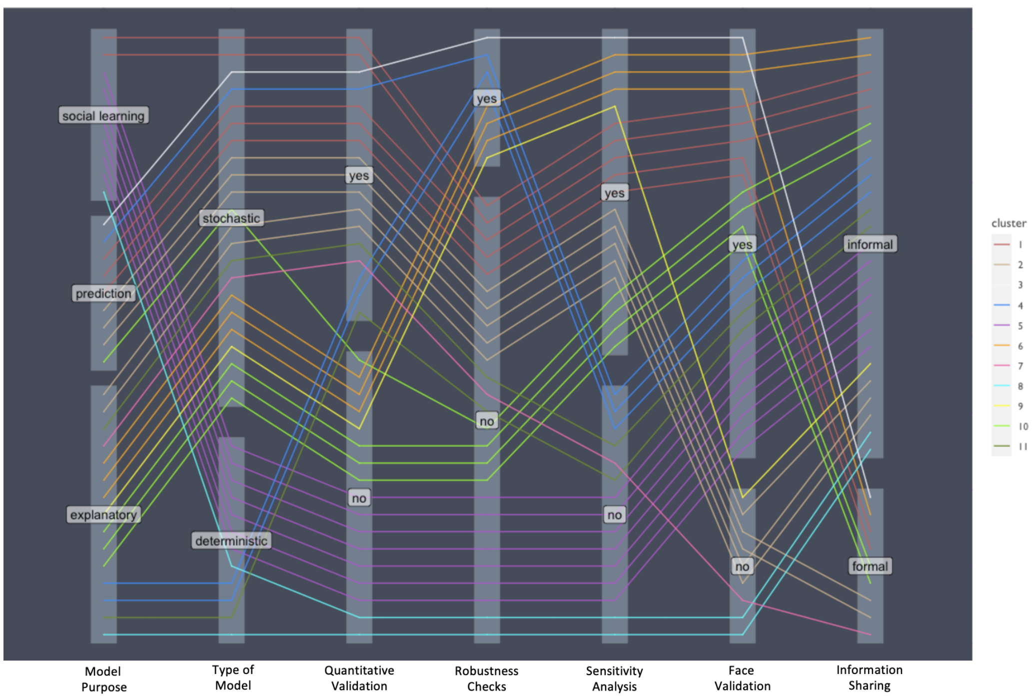

Figure 5: Each line in the parallel coordinate plot represents one policy model and describes the attributes of the different dimensions of the visualization.

The model purpose was determined by using the taxonomy proposed by Edmonds [9], identifying three common purposes in policy modeling: prediction, explanation, and social learning. The type of model indicates whether the model is deterministic or stochastic. Our main outcome variable of interest is information sharing. The majority of policy-modeling projects relay information informally to policymakers by sharing the insights derived from the model through discussions during meetings and workshops. This makes it difficult to evaluate how models are used in practice as it is unclear what information is shared with policymakers. Approximately a quarter of all applications report different approaches to what we categorized as formal information sharing strategies, such as formal policy recommendations, comprehensive reports of the model and its generated results, or providing policymakers with training for using the model later given.

This visualisation should not be over-interpreted as some modelers being more, or less, rigorous about model validation since data accessibility can differ systematically between contexts and may hamper the ability to conduct various model tests. However, little to no validation could affect the inferential capability of the model and pose larger risks for applications in policy-making [53], but we tend to agree with the argument made before us: implemented models that have been formalized are to be preferred over implicit mental models [54]. With this in mind, this plot is especially helpful in elucidating patterns in the interactions between validation and other policy-modeling dimensions.

The first documented purpose in policy-modeling is *social learning*, where simulations are used as a discussion, negotiation or learning tool [9, 49]. The first two applications are stochastic models and belong to cluster 1 (red) which employ relatively much model testing as a validation strategy. However, a clear majority of social learning applications included in this literature review involve deterministic models belonging to two clusters that apply validation strategies with relatively little model testing. Specifically, cluster 4 (turquoise) relies only on face validation, and cluster 5 (purple) does not report any model testing. The information derived from these models and their results was shared through informal discussions with policymakers.

The second model purpose is *prediction*, sometimes also referred to as forecasting to communicate the presence of uncertainty, aims to address inquiries concerning the future state of a given system [9, 55]. Unlike social learning, predictive applications intuitively consist mainly of stochastic models and are distributed across clusters 1 (red), 2 (tan), 3 (white), 4 (blue), and 10 (light green), applying more rigorous testing in their validation strategies. These applications are also well-represented in the category of formal information sharing, meaning that they frequently produce formal policy advice, formal reports, or share models with policymakers.

The third model purpose *explanation*, seeks to provide causal explanations for why some observed phenomena occurs [56, 9]. Explanatory modeling applications tend to be more diverse than both of the previous modeling purposes in all modeling aspects. These applications include both stochastic and deterministic models belonging to all clusters except 1 (red) and 4 (turquoise), indicating a diverse set of validation strategies. Three out of the 15 explanatory applications used a formal information strategy to relay the information produced by the model to policymakers. Lastly, we note that stochastic models tend to employ more rigorous validation strategies compared to deterministic models.

Table 2 provides information on the traceability of the ABMs applied to policy-making. If the model is traceable, it allows for an independent model assessment to understand the model's inferential capabilities and limitations. The frequency table includes information about how many model were uploaded to an online repositories like Github or CoMSES, and how many articles included model documentation like the ODD-protocol in their supplementary material [57]. One publication included a broken URL, which we, therefore, counted as not being uploaded. The majority of the articles (67%) are neither uploaded on an online repository nor include model documentation. Only about 9% included both a model protocol and uploaded the model to an online repository. This finding supports previous concerns raised during the height of the COVID-19 pandemic [12] but could also serve to undermine transparency in political decision-making. Additionally, none of the articles report their model going through a formal accreditation process.

Table 2: Frequency table including percentages of how many models that were uploaded to an online repositories and/or included a model protocol.

Model Traceability	No Protocol Included	Protocol Included	**Sum**
No Repository	67.7%	8.8%	76.5%
Repository	14.7%	8.8%	23.5%
Sum	82.4%	17.6%	100.0%

5 CONCLUSIONS AND FUTURE WORK

We conducted a systematic literature review investigating policy-modeling applications used together with policymakers. This review revealed that ABMs, when used in together with policymakers, have been implemented using a variety of software and applied to support policymakers across a range of policy areas.

We identified several potential challenges and opportunities related to the use of ABMs in policy-making. The involvement of policymakers in policy-modeling is often leveraged by modelers to enhance the validity of models. This is evident in many projects where policymakers are engaged during the design stage, with over 70% of all applications in this literature review including policymakers during both the model design and intervention design phases. Additionally, since policymakers can be considered experts of the target system, informal validation techniques such as face validation – performed in 73.5% of all cases – may carry more weight. However, there are also reported risks where political decision-making and accountability could be undermined, as policymakers might rely more than originally intended on their scientific advisors, expecting them to provide formal policy advice. Furthermore, one account reports concerns where scientists have been perceived to move beyond their facilitative role, actively guiding policymakers toward their preferred outcome, a perspective not necessarily shared by the policymakers. This indicates that the continued discussions pertaining to the role of the modelers in policy-making and ethical considerations are needed.

Many of the policy models used for policy-making quite naturally aim to provide broad societal benefits for the population at large, which could make the participation of stakeholders in the policy-making process challenging. Survey methodology could potentially address this challenge and is already commonly applied in such projects – 32% of the applications in this study – where statistical inference could be leveraged to consider general public opinion in policy-modeling. Several modelers also report numerous challenges related to the successful retrieval of appropriate secondary data from stakeholders and policymakers, highlighting the importance of timely investigation into data accessibility.

There are three different modeling purposes documented in the applications included in this literature review, social learning, prediction, and explanation. We conclude that model related factors, such as purpose and whether the model is stochastic or deterministic, contribute to the adoption of distinct validation strategies and the dissemination of information to policymakers. A majority of applications share information informally, making it challenging to trace the type of information used to inform policy prescriptions. For instance, policy models used in policy-making for the purpose of social learning tend to be mainly deterministic. They adopt relatively little model testing and are exclusively communicated informally. Conversely, predictive models are stochastic and tend to adopt more formal model testing and information sharing strategies. Explanatory modeling is the most diverse of the recorded model purposes. It uses both deterministic and stochastic models, including validation strategies with varying amounts of model testing. It has been reported to disseminate information to policymakers both formally and informally. While data availability determines how model testing can be performed, the risk of poor model fit increase in the absence of sufficient validation.

The traceability of policy models used for policymaking is also low. 9% of the articles included both a model protocol and uploaded the model to an online repository, while the majority of the articles 67% neither uploaded their models to an online repository nor included model documentation. Without traceable model documentation and accreditation after the completion of a project, policymakers might find it difficult to motivate their decision as time pass. This could make the policy-making process less transparent. Applications where all these factors are combined could pose a particularly high risk when used in policy-making. These factors include models that have undergone little to no testing, the absence of any model documentation and accessibility, and the informal sharing of simulation results with policymakers. In the worst case scenario, modelers might be the only actors able to account for how and why a policy decision was reached.

With these findings in mind we reiterate that applied policy-modeling rests on a symbiotic relationship between scientists and policymakers. This means that modeling challenges tend to propagate into political and societal challenges and *vice-versa*. For instance, issues like data quality could negatively affect the inferential capability of the model, resulting in sub-optimal or even faulty decision-making. Aspects like poor model traceability could negatively affect transparency in the decision-making process, and potentially accountability, as improper model documentation could mean that policymakers find themselves having a difficult time motivating their decisions. Furthermore, diffuse stakeholder groups and limited participation might negatively affect model validity and limit democratic participation in the decision-making process.

However, all of these negative effects also operate in the opposite direction. Increasing participation, model traceability, and formal information sharing serve to have positive effects on the political and societal aspects. Consequently, beyond challenges, we see tremendous opportunities for the use of ABMs in policy-making. Leaning on the experience gained from previous applied policy modeling projects, we propose: (1) Anchoring the project within the institutional setting in its early stages to secure commitment from policy-makers. (2) Inquire about data availability at the start of the project to establish a plan for model calibration and validation. (3) Provide policymakers with ample model documentation, detailed model specification, underlying assumptions, and results. This ensures that policymakers possess the requisite information to autonomously motivate their decision-making.

In light of these findings, promising directions for future research emerge, encompassing already ongoing ethical dialogues regarding the scientist's engagement in policy-making, strategies for public participation in policy-modeling processes, and the development of reviewing tools for applying ABMs in policy-making.

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AUTHOR BIOGRAPHIES

MICHAEL BELFRAGE holds a MSc in computational social science with focus on social networks and peer influence estimation. Currently, he is a PhD-candidate at Malmö University, Sweden. His research interests include agent-based simulation, graph theory, and computational politics. michael.belfrage@mau.se.

FABIAN LORIG holds a PhD in computer science with focus on agent-based simulation. He is an assistant professor at Malmö University, Sweden and his research interests include the use of agent technology for decision support with applications in logistics, transportation, and healthcare. fabian.lorig@mau.se.

PAUL DAVIDSSON is a professor at Malmö University, Sweden, as well as the director of the Internet of Things and People Research Center. His research interests include the theory and application multi-agent systems, Artificial Intelligence, and Internet of Things. paul.davidsson@mau.se.