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*Research Article*

# Simulation, Science, and Stakeholders: Challenges and Opportunities for Modelling Solutions to Societal Problems

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The article outlines an approach to computer modelling called "human simulation," whose development has been explicitly oriented towards addressing societal problems through transdisciplinary efforts involving stakeholders, change agents, policy professionals, subject matter experts, and computer scientists. It describes the steps involved in the creation and exploration of the "insight space" of policy-oriented artificial societies, which include both analysing societal problems and designing societal solutions. A case study is provided, based on an (ongoing) research project studying "emotional contagion" related to misinformation, stigma, and anxiety in the wake of the COVID-19 pandemic, along with lessons learned about some of the challenges and opportunities facing scientists and stakeholders trying to simulate solutions to complex societal problems.

## 1. Introduction

The task of finding solutions to complex societal problems calls for tools that can provide insight into the mechanisms by which, the conditions under which, and the extent to which nonlinear socioecological systems can adapt. The good news is that there are computational modelling and simulation (CMS) tools, especially agent-based modelling (ABM), that are designed specifically for understanding and explaining such complex adaptive systems [1, 2]. Although the use of these tools to address real-world societal problems is increasing rapidly [3–6], the bad news is that progress is held up by challenges related to the psychological and sociological realism of "artificial societies" and by challenges related to engaging stakeholders in participatory modelling [7]. As we will see, these challenges are closely linked and taking full advantage of opportunities for the practical application of CMS methodologies to the task of solving societal challenges will require a more careful and rigorous linking of stakeholder participation strategies to the scientific process of developing and deploying adequately realistic computational models.

The first major section of this article outlines an approach called "human simulation," whose development has been explicitly oriented towards addressing societal problems through transdisciplinary efforts involving stakeholders, change agents, policy professionals, subject matter experts, and computer scientists [8]. A more detailed description of the steps involved in the creation and exploration of "insight space"—which involves both analysing societal problems and designing societal solutions—is provided in the second major section. The third section provides a case study, illustrating this approach and reporting on lessons learned in an (ongoing) research project studying emotional contagion in the wake of the COVID-19 pandemic. I conclude with a summary of some of the challenges and opportunities facing those of us who want to bring together scientists and stakeholders to simulate solutions to complex societal problems.

## 2. The "Human Simulation" Approach

The collaborative approach outlined and illustrated in *Human Simulation: Perspectives, Insights, and Applications* [8], is one way of addressing the challenges (and pursuing the opportunities) identified briefly above. That volume describes several models developed using this approach, but it is important to note that the latter has been developed, tested, and expanded within the context of several interrelated research projects [9] that have produced a wide variety of policy-oriented computational models that provide platforms for exploring societal problems related to topics such as human terror management in response to threats such as contagion or natural hazards [10], the mutual escalation of xenophobic intergroup conflict [11], the role of education and existential security in secularisation [12], the integration of minorities in western urban contexts [13], morality and (non)religious altruism [14], and social networks in pluralistic cultures [15]. Below I will spell out this approach in more detail, focusing particularly on the interaction of stakeholders and scientists in the process of analysing problems and designing solutions, but in the remainder of this section, I want to highlight some of the reasons for calling it "human" simulation.

*2.1. Simulation of Humans.* First, and perhaps most obviously, this approach simulates humans. That is to say, it constructs simulated agents with human variables (e.g., opinion and orientations), places them into social networks, and explores their behaviours and interactions with each other and their virtual environment under an array of parametric conditions. One of the major challenges here is a concern (or outright objection) sometimes expressed by stakeholders and subject matter experts in the humanities and social sciences that humans are simply too complex to be simulated.

It is important to acknowledge both that humans are indeed astonishingly complex and that CMS techniques cannot (currently) model each and every aspect of human life. However, it is equally important to explain why the latter is not necessary in order to develop useful models of humans (and the societal problems within which they find themselves). In fact, such comprehensive modelling would be counter-productive. Andreas Tolk refers to computer models as "purposeful abstractions" [16], and we can add that their being-abstract is a condition for their being-useful for a purpose. A geographical map can be useful for the purpose of navigating from New York to Los Angeles (for example), but such usefulness depends on it achieving the right level of abstraction. The map user needs to know where the rivers and mountains are but not the rivulets and molehills. A map that included all of the latter would cease to be useful.

What is the right level of abstraction for computer modelers, data scientists, and operations research scholars interested in collaborating to solve complex *human* societal problems? It depends. The "Goldilocks" level of abstraction cannot be determined in advance but must be discovered in dialogue among relevant stakeholders. However, we can say in advance that modelling whose purpose is policy-oriented is likely to require simulations of human behaviours and interactions that take into account insights from disciplines such as biology, psychology, anthropology, sociology, geography, and economics. This does not mean that all of the insights of these fields must be included, only that those insights ought to shape the conversation about the level of abstraction necessary for making the model useful for the purpose of solving societal problems.

Many early social simulations, especially those involving game theoretic approaches, presupposed that real-world humans are "rational actors" and modelled their artificial agents accordingly. Today, most students of human nature agree that human behaviours are not simply the result of internal calculations of utility functions, but rather emerge out of a complex set of physically embodied and socially embedded motivations and biases. This means that simulations of humans should typically involve cognitive architectures and social networks that take seriously research on the phylogenetic heritage and cultural entrainment practices that inform human decision-making in the real world [17], and aim for appropriate levels of social psychological realism in the simulated agents populating an artificial society [18].

*2.2. Simulation by and for Humans.* But even this is not sufficient. The task may already appear insurmountably complex, but we must also face a second challenge (which is related to a second rationale for the name of the proposed approach): simulations of humans are created by and for humans. This means that the recognition that human behaviours are biased and motivated also applies to the behaviour of transdisciplinary policy-oriented computer modelling and simulation. No doubt this is a challenge, any solution to which will likely require engaging in debates in the philosophy of science about human rationality, the tension between subjectivity and objectivity, and the nature of science [19–21]. In this context, however, I want to highlight the opportunity that CMS methods provide for surfacing biases and motivations related to the role of human assumptions and purposes in the process of modelling societal problems and solutions.

On the one hand, the conceptualization and formalization required in the construction of a computational architecture of a complex social system enables and encourages its creators to be explicit about their *assumptions* related to human (and other) variables in their model. Each variable and behaviour must be clearly defined and operationalized by the modelers (and hopefully stakeholders) involved. The human simulation approach includes ongoing reflection on the extent to which the biases of team members are at work in such definitions and operationalizations. One way of expressing this in the context of the current article is to say that the very identification and articulation of a societal problem—as a *problem*—can (and should) be problematized and discussed during the model building process.

On the other hand, the *purposes* of a computational model should (and can) also be surfaced and discussed throughout the development and deployment process. Whether or not they are explicitly policy-oriented, models built by humans are always for something. They are designed with some goal in mind (e.g., an explanatory, descriptive, predictive, or interpretive goal). The current article is concerned with models that aim at solutions to societal problems and so the main point to make here is that the very identification and articulation of a societal solution—as a *solution*—is already based on a human judgement about an ideal (or at least a better) future. But humans disagree about such things, which is why it is important to include a range of stakeholders in the process of model construction and simulation experiment design.

This raises serious ethical questions that are important to incorporate into human (all too human) simulation [22–24]. Some CMS tools have the capacity to reveal mechanisms underlying societal changes and even to predict the consequences of altering agent and group variables and environmental conditions. Like other potentially powerful technologies (e.g., nuclear power and genetic engineering), they can be used for good or ill. The key point here is that humans will disagree on which outcomes are good and which are ill. While some might want to use models of ideological polarization (for example) to mitigate what they see as the negative effects of extremist views, others might use the same model to promote polarization in order to destabilize a society. While including a variety of stakeholders into model building and simulation design will not solve this problem, it can at least help to surface some of the relevant assumptions and purposes that may otherwise have remained hidden. This is one reason why more and more modelling teams are working to develop better participatory strategies for involving stakeholders in the simulation of socioecological problems and their solutions [24–32].

*2.3. Simulation with Humanists (and Social Scientists).* A third reason for referring to this approach as "human" simulation is to highlight the importance of including experts from the humanities and social sciences within the transdisciplinary teams attempting to address societal challenges. In other words, in addition to policy stakeholders and change agents, when possible, one should also invite scholars with expertise in human and social systems into the model building and simulation design process. This is a necessary step on the path towards more realistic cognitive architectures and artificial societies. Moreover, policy professionals concerned about addressing particular societal problems are quite often trained in these disciplines and so designing a process that more easily incorporates humanities and social scientific sensibilities just makes good sense.

In my experience, a good strategy for introducing humanists and social scientists to CMS is to begin with system-dynamics models (SDMs). Such models, which are all about the dynamics involved in complex changing systems, can feel more intuitive and are easier to understand for those new to these methodologies. Moreover, the extraction of relevant knowledge about the dynamics of social systems from historians, philosophers, psychologists, anthropologists, sociologists, and scholars from related disciplines is somewhat more straightforward in the construction of SDMs. Our teams have worked with experts in these and other fields to develop models that have been able to simulate major shifts in human civilizational forms, including the Neolithic transition from hunter-gatherer to sedentary-agricultural lifestyles [33] and the 1$^{st}$ millennium BCE transition from pre-Axial to Axial Age societies in west, south, and east Asia [34]. A more relevant example for our present purposes is a recent model of the modernity transition, which simulated the emergence of secular (or post-supernatural) cultures [35]. Each of these models processes by which a complex social system adapts by transitioning to a new mode of cohesive organization and functioning.

Not all societal problems require such radical transformation, but we can learn something about the capacities and tendencies of social systems by modelling those that do. SDMs are indeed a good place to start, but achieving the level of realism discussed previously, which is important both for scientific and stakeholder engagement reasons, is better facilitated by agent-based models (ABMs). Real societies consist of actual agents who interact in spatiotemporal environments, and "agent-based" models enable the exploration of links between the micro-, meso-, and macro-levels of societies in a way that is not possible with SDMs. Most of the models constructed by the teams involved in the overlapping research projects [9] that led to the approach outlined in *Human Simulation* [8] have been ABMs of a certain sort; namely, multiagent artificial intelligence (MAAI) models, which are strongly focused on cognitive and social realism [36].

Another advantage of simulating with scholars from the humanities and social sciences is that such collaboration can foster transdisciplinary conversations about concerns in the philosophy of science that are shared by scholars in computer sciences and other STEM disciplines. Artificial societies populated by simulated human agents who interact under a wide variety of parameters can provide a platform for discussing and exploring philosophical issues, including epistemology and ontology [37–39], as well as the ethical issues noted earlier. This kind of "experimental" philosophy of science—playing with artificial ontologies, epistemologies, and moralities—offers a new way of gently transgressing some of the old intellectual and political (and even economic) boundaries between what used to be called the "hard" and the "soft" sciences. "Human simulation" is no panacea, nor is it likely to bring philosophy of science debates within and between fields to closure, but it does provide a set of tools that can facilitate the kind radical transdisciplinary collaboration that will be required to find solutions to many of the complex societal problems currently faced by our species.

## 3. Analysing Problems and Designing Solutions

In this section, I outline the general procedure for navigating what has elsewhere been called the "insight space" provided by the human simulation approach to computational models aimed at social simulation [7]. The navigation of this space moves (often backward as well as forward) through five distinct but interrelated phases: analysing a problem situation, creating a problem space, selecting a specific problem, designing a solution space, and critique and iteration. In the next section, I will illustrate these phases in relation to an ABM whose assumptions are grounded in "emotional contagion" and other social psychological theories and whose purpose is to shed light on solutions for a set of societal problems that have emerged with particular intensity in the wake of the COVID-19 pandemic. First, however, it is important to introduce some of the *human factors* that play a role in the development and deployment of such models, factors that inevitably shape the material decisions and formal processes of both scientists and stakeholders involved in transdisciplinary collaborative social simulation.

The first phase in the navigation of the insight space is *analysing a problem situation*. The task here is identifying a societal problem and finding stakeholders who are ready, willing, and able to look for solutions using CMS methodologies. At the beginning, the problem may be relatively general and part of the reason for bringing in stakeholders early in the process is to adequately identify the lines of convergence and areas of divergence within and across groups of stakeholders (including subject matter experts and change agents). Selecting the right balance of stakeholders can be tricky because too much convergence in the team can lead to simplistic models grounded in groupthink and too much divergence can lead to disruptive conflict that makes progress impossible. Here, the human factors at play in the process can include resistance to change, on the one hand, and overly enthusiastic attitudes toward change, on the other. Stakeholders and scientists are human too, and so they will bring with them baggage related to their psychological and political worldviews and alliances. Unpacking and observing the contents of this baggage requires discretion and trust-building with the team, but if done in a way that is appropriate to the context it can lead to far more self-reflective analyses of the problem situation.

The next step is *creating a problem space*. During this phase, which typically overlaps with the first and anticipates the remaining phases, the task is to construct the conceptual and computational state space within which the societal problem(s) can be specified and studied. The goal is to formalize the key boundary conditions of the problem space, which requires the identification of leading mechanisms of change in the complex social system as well as the relevant variables, interactions, and parameters that play a role in conditioning those changes. Human factors that influence this phase may include cognitive biases that lead participants to under- or overinterpret the scope of the problem or the importance of particular variables or mechanisms. As in the previous phase, ethical assumptions as well as assumptions about human, society, and nature are always and already at work. Doing our best to surface them and to remain open to their contestation makes us better scientists and stakeholders and is more likely to lead to plausible computational architectures with useful problem spaces.

A third phase involves *selecting a specific problem*. Once the problem space has been constructed, the team needs to specify a specific problem within that state space. In fact, the same state space may be useful for exploring a variety of societal problems but we have to start somewhere. Specifying a problem requires selecting the concrete agent variables, mechanisms, interaction rules, and parameters that will be used to structure the simulation experiments. Here, we must already anticipate the fourth phase because the design of these experiments also requires us to decide what will count as a solution to the societal problem modelled in the artificial society—if we can find one (or many). One of the human factors that can colour this part of the process is the temptation to settle for societal problems that seem relatively tractable instead of tackling more important and complex challenges. This sort of transdisciplinary effort can be exhausting, and it is worthwhile for project leaders to plan ahead in order to provide team members with the time and space (and resources) they need to think and talk through the implications of settling on one of the specific problems at hand.

During the fourth phase the team's task is *designing a solution space*. Some stakeholders might wish we could start here, since their primary focus is on solving the actual societal problem. In one sense, we do start here, at least imaginatively; anticipating this phase has a kind of retroactive effect on the whole process up to this point. This phase involves specifying the evaluation criteria for solutions and identifying direct metrics that can be matched to existing data or producing new data that can inform the calibration, verification, and validation of the model and simulation experiments. Among the human factors that can surreptitiously complicate this process are biases or motivations that lead to an obsession with focusing on a particular kind of solution space (that may have worked in the past) rather than brainstorming novel possibility spaces that could reveal ground-breaking opportunities for promoting salubrious societal change. Ethical assumptions and moral intentions are ever present here as well, and it is important to have the tough conversations about exactly why—and for whom—we think a particular solution is salubrious.

A fifth and final phase in the navigation of the insight space opened up by the human simulation approach to CMS is *critique and iteration*. The task in this context is evaluating the experience (or "feel") of the model and the results of simulation experiments to determine whether the solution space is adequate or whether the specific problem identified earlier needs to be reframed. As in the earlier phases, it is important to attend to the human factors that can undermine or short-circuit the process. Exhaustion is particularly likely to take a toll on participants during this final phase of model construction and testing. But this is where team-building efforts can pay off if both the stakeholders and scientists involved have learned to give and take critique and to encourage one another to stay focused on their shared concerns about finding concrete solutions to specific societal problems.

The process of disseminating the results of a computational model and its simulation experiments might be considered an additional phase of the process, but once these results are published, whether in academic journals or in policy white papers, they take on a life of their own. This is all the more reason to pay careful attention to and make as explicit as possible the team's assumptions and purposes as they come to light and are articulated in the five phases of navigating the insight space of the model.

## 4. Case Study: Modelling Emotional Contagion during a Pandemic

As noted above, the international teams that have developed the human simulation approach have constructed a wide variety of policy-oriented computational models. I have illustrated elsewhere how the five phases just outlined played out in our development and dissemination of a model of mutually escalating religious conflict [40]. In this context, I take on a more difficult, but in some ways more fitting, task: providing critical reflections and reporting lessons learned during the *ongoing* process of constructing a model of a societal problem that has altered the global social landscape since its emergence in early 2020. This is more difficult because we are still in the process of surfacing our assumptions and attempting to articulate our purposes for the model. It may be more fitting because it exposes the kind of vulnerability that characterizes this process when the navigation of a model's insight space is still underway.

*4.1. The Emotional Contagion (EmotiCon) Project.* The ABM that will serve as a case study here is part of a broader research project called "Emotional Contagion: Predicting and Preventing the Spread of Misinformation, Stigma, and Fear during a Pandemic" (EmotiCon), which is funded by the Research Council of Norway, 2020–2022. CMS techniques have been widely used during the pandemic to produce epidemiological models and to forecast the spread of COVID-19. The policy-oriented goal of many such models is to "flatten the curve" of disease contagion so that the number of cases does not rise too quickly. Protective measures such as face masks and social distancing can slow down (and spread out over time) the cases of contagion so that they do not pass a threshold beyond which healthcare systems collapse.

The EmotiCon project was designed to help discover some of the mechanisms by which misinformation, stigma, and fear spread in Norway in the wake of the pandemic. In this case we are interested in flattening the curve of *emotional* contagion. If psychologically and politically problematic attitudes and behaviours rise too quickly, a population may reach a threshold beyond with social cohesion begins to deteriorate rapidly and social conflict is more likely to erupt. The main goal of the project is to develop user-friendly multiagent artificial intelligence tools that will enable Norwegian municipalities and other governmental agencies to (1) analyse and forecast the societal effects of their public health responses and social countermeasures to pandemics and (2) experiment with alternative intervention strategies and protective measures for "flattening the curve" of psychologically and politically debilitating social contagion before trying them out in the real world (Figure 1).

The EmotiCon project has three broad components: social media data gathering and analysis, panel survey data gathering and analysis, and the construction of an ABM. The first two components, which are now basically complete, were designed to help in the verification and validation of the last component, which is well underway. The social media analysis utilized natural language processing techniques, which were trained on the Norwegian language, to create embedded word vectors representing the relationships among terms and concepts discussed online. Using this data, we created psychographic profiles of social media users that include variables such as moral foundations, political values, topics of interest, network placement, and beliefs. These data have been analysed to identify key emotional dynamics, rates of online information spread, and other features of the population's response to COVID-19 over time. The panel surveys, which provide a representative sample of the Norwegian population, were executed in October 2020 and April 2021. The surveys contained previously validated scales such as the "emotional contagion scale" [41], but we also designed several original questions prepared for our specific purposes. The purpose of the current article, however, is not to describe or report on these data analyses but to reflect on our ongoing process of navigating the insight space of the models under construction.

*4.2. Human Factors in the EmotiCon Modelling Process (So Far).* So, what lessons are we learning about the challenges and opportunities associated with simulating solutions to societal problems with transdisciplinary teams of scientists and stakeholders? What human factors have we discovered shaping our work so far? And what insights dare we hope our future simulation experiments will bring? What tangible guidance might we offer based on these and other collaborative modelling experiences?

*4.2.1. Phase 1: Analysing a Problem Situation.* Broadly speaking, our real-world target for this social simulation is the spread of emotional contagion (in the sense described previously) in Norway in the wake of the COVID-19 pandemic. As part of the grant-writing process, we sought out and secured the participation of ten stakeholders, all health care policy professionals representing municipalities across Norway. We held video-conference discussions with them during the planning process and have continued to engage them during the completion of the first two data-gathering components of the project. Given the time constraints of the emergency call for proposals from the Research Council of Norway in early 2020, we were not able to explore in detail how much convergence or divergence we could expect among our stakeholders. However, our experience so far has been that there is a relatively strong convergence in relation to concern about the seriousness of the societal problem, and some minor divergence in relation to which aspects of (and potential solutions to) the problem ought to be our focus. As we move into the next stages of ABM development, we anticipate more areas of convergence and divergence will be discovered. Up to this point, our conversations have mostly been about the rationale and strategies for the data analysis. However, over time we have

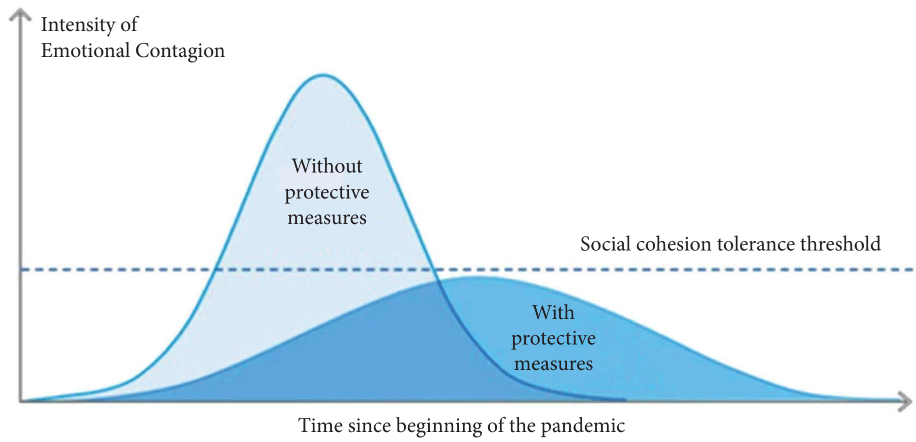


Figure 1: "Flattening the curve" of emotional contagion.

learned that it is important to discuss the *purposes* of the model(s) under construction as soon as possible, anticipating the "solution space" that will need to be developed in phase 4. Social simulations can have a wide range of purposes [42, 43], and explaining options and managing expectations (about "prediction," for example) is a crucial step in communicating with stakeholders during this early stage. The pandemic itself has hampered our capacity for team-building, which we have found is far more difficult through relatively short video-conferencing events compared to longer, face-to-face meetings. We still hope to be able to facilitate the latter at some stage in the ABM construction process, at which point it will be easier to share and discuss the human factors shaping our convergent (and divergent) concerns about the problem situation.

*4.2.2. Phase 2: Creating a Problem Space.* This phase is well underway and is being informed by our anticipation of (and initial reflection on) the next two phases, namely, selecting a specific problem and designing a solution space (described in the following sections below). It is important to keep in mind that a "problem space" is not the same thing as a "problem." CMS tools typically enable us to specify and explore a *set* of questions within a single model. This second phase is about constructing the state space within which problems related to the phenomenon of interest (emotional contagion in the wake of a pandemic) can be analysed. After about six months of discussion, we decided to construct two distinct but interrelated ABMs (described briefly in phases 3 and 4 in the following), each of which will have its own problem space. However, they share some of the same boundary conditions, e.g., the contemporary Norwegian population and an 18 month time frame. They also share general assumptions about the leading causes of change (e.g., social psychological mechanisms and network effects) and are focused on agent variables that can be calibrated using the data gathered from the social media and panel survey data (e.g., susceptibility to emotional contagion and demographic variables). Based on past experiences with subject matter experts in other modelling projects and in meeting the media when disseminating project results, we recommend that time be set aside early (and often) in this process to discuss the general ethical issues permeating and surrounding the societal challenges being modelled as well as the specific moral concerns of relevant stakeholders. The EmotiCon team has rigorously discussed our own biases about the nature and dynamics of key factors such as emotional contagion and epistemic vice, and we are in the process of articulating our assumptions and operationalizing key variables in each of the models.

*4.2.3. Phase 3: Selecting a Specific Problem.* As indicated previously, we decided to develop two models with different problem spaces, which then opened up the possibility of identifying and selecting two different specified problems. The first model will be an adaptation of a previous model (HUMAT) developed as part of an earlier grant [44]. The agent architecture and network structures of that model are informed by theories about the cognitive dissonance mechanisms that shape the satisfaction of human experiential, social, and value-oriented needs as well as ways in which dissonance reduction strategies are influenced by various types of social interaction. This architecture is being expanded to include variables related to our new data (emotional contagion and social cohesion motivations), which will enable us to answer specific research questions of the following sort: which psychological mechanisms and social interactions played a dominant role in driving the spread of misinformation and conspiracy theories in Norway from the fall of 2020 through the spring of 2021? All of this depends, of course, on our eventual success in the verification and validation processes in phase 5. The second EmotiCon ABM will also involve the adaptation of a previous model from a previous grant, in this case a model of mutually escalating religious violence (MERV). That model included environmental parameters that allow variations related to contagion, predation, cultural, and natural threats [11]. The cognitive architecture of the agents in MERV was informed by social psychological theories such as terror management theory, social identity theory, and identity fusion theory, all of which identify cognitive systems have been empirically shown to mediate human reactions to threats (such as a pandemic). This model is being expanded to incorporate the relevant additional variables mentioned previously, which will help us address specific questions of the following sort: under what environmental conditions are pandemic-induced anxieties and in-group antagonism likely to spread in the Norwegian population? The problems identified by these models are quite complex and it is not yet clear whether they will be tractable, but they are incredibly important and we are throwing our energy into tackling them.

*4.2.4. Phase 4: Designing a Solution Space.* In a sense, this phase is always in the back—and *sometimes* in the front—of our minds as we work with stakeholders through the first three phases. Here too, it is important to remember the distinction between a "solution space" and a "solution." The former is a kind of state space, which may contain singularities and attractors that in turn make possible the discovery of a variety of solutions under different simulation experimental conditions. But how would we even know that we had found a solution? We must make the metrics for our evaluation criteria explicit. In the current case, these criteria are guided by the new social media and survey data we gathered and analysed for this purpose. The validity of both of our ABMs will be judged by their capacity to simulate the macrolevel shifts in the Norwegian population (represented in the real-world longitudinal data) from the microlevel behaviours and mesolevel interactions of their simulated agents (guided by variables and rules based on the relevant theories). Solutions in the HUMAT and MERV-based models will be evaluated by the extent to which their computational architectures can generate (or "grow") the patterns observed in Norway in 2020 and 2021 within an artificial society (or digital twin) composed of simulated Norwegians. As indicated previously, we are not yet at the stage of working through the solution space with the EmotiCon project stakeholders. However, based on earlier modelling experiences we have followed our own advice and brainstormed with them about the evaluation criteria for "solutions" (e.g., feasibility in a Norwegian public health context) and datasets that could be used in calibration and validation (e.g., microdata available from the Norwegian Centre for Research Data). The team continues to discuss its own (and others) biases as we attempt to make explicit both the ethical assumptions and motivations that shape the structure of our proposed solution space and the overall purpose of our modelling efforts: finding solutions to societal problems related to the devastating impact of global pandemics.

*4.2.5. Phase 5: Critique and Reiterate.* We are not yet at the stage of designing simulation *experiments*, but we anticipate working with our stakeholders to construct optimization experiments that can help identify the conditions under which—and the mechanisms by which—various types of emotional contagion increase (or decrease) in the population. Our Norwegian health professional stakeholders will play a crucial role in assessing the look, feel, and experience of the model and the plausibility of the results of the simulation experiments. It may well be that the solution space we have constructed is inadequate and we need to back up to phase 4 (or even one of the earlier phases). Our teams have sometimes had to admit defeat at this stage of the human simulation process, which is to be expected if we take seriously that it involves real *critique* and the determination to keep *reiterating* until both stakeholders and scientists are sufficiently satisfied that the causal architecture of the artificial society is adequately verified and validated in relation to the evaluation criteria outlined in phase 4. Elsewhere, Wesley J. Wildman has compared the relationship of computer scientists and humanities subject matter experts to pandas: both are notoriously difficult to mate. He argues that successful transdisciplinary engagement depends on getting the right mix of people in a comfortable and quiet environment and setting up procedures that facilitate their getting to know each other and learning enough about the values and methods of their respective disciplines so that they can work together [45]. This is why it is so important to find open-minded and passionate stakeholders and provide them with adequate time, resources, and guidance in a context that fosters collaboration. The health policy professionals in the user group for the EmotiCon project have shown enthusiasm so far in the process, and we hope to havein-person participatory modelling events that will summarize and integrate phases 1–3, finalize phase 4, initialize phase 5, and develop strategies for disseminating our results to other stakeholders and the wider public.

## 5. Conclusion

In this article, I have summarized the "human simulation" approach to computer modelling [8], which strives to address societal problems through transdisciplinary efforts involving stakeholders, change agents, policy professionals, subject matter experts, and computer scientists. I briefly described the five main (overlapping) phases that are involved in the creation and exploration of the "insight space" of policy-oriented artificial societies, paying special attention to the tasks of analysing societal problems and designing societal solutions. The case study used to illustrate this approach, and the "human factors" that shape it at every turn, was based on an (ongoing) project in which our team is attempting to understand the spread of "emotional contagion" in the wake of the COVID-19 pandemic. CMS methodologies have been used by other teams to study how the pandemic has impacted society in various ways [46–50] and to study the dynamics of emotional contagion both offline and online [51–57]. What we hope to contribute with the EmotiCon models, however, are new insights into how to "flatten the curve" of growing anxiety, stigma, and misinformation so that populations do not pass a threshold beyond which social cohesion begins to unravel.

My overall goal in this context has been to highlight some of the lessons we have learned so far along the way in EmotiCon and in other projects, focusing on the challenges and opportunities involved when scientists and stakeholders work together to try and simulate solutions to complex societal problems. Success in the latter will require the ongoing development and deployment of innovative strategies for working with subject matter and policy experts with knowledge in the relevant social scientific or humanities disciplines, in order to build simulations of realistic human agents in realistic social contexts in a way that surfaces the biases and hopes of those by whom and for whom the models are constructed. As with other technologies, such as genetic engineering or nuclear power, CMS tools can be used for good or ill. We plan to use the models to mitigate emotional contagion, but others might use it to amplify the spread of misinformation, stigma, and anxiety in particular geographic regions. Our team has ongoing conversations, both internally and externally, about these and other ethical issues associated with our models. Such discussions do not provide immunity from bias or misuse, but by making our own assumptions and purposes as clear as possible, we make it easier for others to challenge them, which in turn can facilitate wider public debates about proposed solutions to shared societal problems [29].

## Data Availability

No underlying data were collected or produced in this study.

## Conflicts of Interest

The author declares that there are no conflicts of interest regarding the publication of this paper.

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