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PANEL ON ETHICAL CONSTRAINTS ON VALIDATION, VERIFICATION, AND APPLICATION OF SIMULATION

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ABSTRACT

Today's challenges must be addressed as socio-technical systems, including insights from the social sciences and humanities to adequately represent the human components. As results of simulations are increasingly driving and justifying political and social decisions, it is important to validate and verify (V&V) simulation and data. However, the understanding of what establishes truth and how these views impact validation differ between the social and technical partners. Therefore, we must expand our view of V&V. The panel provides various use cases and derives ethical questions related to supporting universities during the COVID-19 pandemic, creating multi-disciplinary teams with diverse viewpoints, challenges of using validated insights without critical evaluation, and lack of broadly accepted scientific measures to connect social models and empirical data. We conclude that the role of V&V must be reemphasized, that its social-theoretical implications must be better understood, and that it should be driven by an overarching metaethical framework.

1 INTRODUCTION

When applying modeling and simulation to address big challenges of today, these problems will not only be increasingly complex, but they will also address social science challenges and aspects of the humanities, as we are looking more and more at problems in a socio-technical context. Current methods and assumptions on how to conduct verification and validation (V&V) are rooted in the physics-based application domain, in which simulation has many success stories. In the context of V&V of simulation solutions, we often use the explanation that verification answers the question *"do we build the model right?"* while validity answers the question *"do we build the right model?"* In other words, verification focuses on the transformational accuracy while validation focuses on the behavioral or representational accuracy (Balci 1998). According to Brade (2004), the credibility of a model is based on the perceived suitability and the perceived correctness of all intermediate products created during model development. The correctness and suitability of simulation results require correctness and suitability of the model and its embedded data, but also suitable and correct runtime input data and use or operation of the model. V&V

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aim to increase the credibility of models and simulation results by providing evidence and indication of correctness and suitability. We ensure that we use a valid simulation implementing the correct model, use the right data, and apply the model in the right context. Recent work on trust in simulation models, such as provided by Yilmaz and Liu (2020) and Harper et al. (2021), are contributing to this foundation.

These pillars remain the same when looking at socio-technical systems, which bring humans and technology together as interconnected elements of a common systems view, but the view on V&V in the social science and humanities differ from the traditional approaches. The use of empirical data and how truth is understood are often driven by postmodern ideas that need to be aligned with the positivistic views predominately applied in technical systems. These views also influence the understanding of what models and simulation results are valid and justified to drive political decisions. Furthermore, our understanding of what establishes ethical conduct in M&S is focusing on the professionalism in client relations or implications of ways of using simulation results. We argue that it is important to include a broader meta-ethical framework – enabling study of the meanings of ethical terms, the nature of ethical judgments, and the types of ethical arguments – for discussing the development and deployment of artificial societies and social simulations (Shults and Wildman 2019). In this way, bringing ethical assumptions to the surface, related to both presuppositions within the model and the purposes of simulation experiments, forces those involved in model construction to take responsibility for their verification and validation. As such, we may have to look to extend not only our understanding of V&V, but we may have to extend our Code of Ethics (Ören et al. 2002) as well to address such ethical considerations.

To motivate such extension in our viewpoints as well as in the education of simulation scholars and practitioners, within our panel we are looking at four use cases and their ethical questions. We start with some questions we encountered in our recent efforts to support the battle against COVID-19, when we provided an open-source model for universities to evaluate the possible effects of interventions of the administration on the wellbeing of students, faculty, and administration, but also on the university as an organization. As challenges such as these are complex, you usually have to bring a group of interdisciplinary experts together. The second use case looks at challenges arising from such collaborations, here in the context of modeling religious conflict and minority integration, and evaluates the usefulness of a six phased approach to guide experts conducting such studies. All of these complex challenges have a human component, so that social sciences and insights from the humanities are needed. The philosophical debates about truth and validation are often significantly different from those in physics-based simulation challenges. Some of the resulting challenges for validation are captured in the third use case, providing examples from opioid misuse studies as well as simulation efforts of the early phases of the pandemic. Finally, the last use case looks at challenges when using modeling and simulation to address some of the big societal problems, using the example to understand aspects of cultural evolution. This use case makes the challenge of constructivism on validation evident.

2 ETHICAL TRADE-OFFS BETWEEN VALIDATION AND ACCESSIBILITY (WILDMAN)

2.1 Use Case

As the seriousness of the SARS-CoV-2 pandemic became evident, universities began scrambling to figure out how to maintain operations without endangering vulnerable or elderly people either on campus or in neighborhoods surrounding the campus. Some universities had the means to create computational simulations as adjuncts to strategic reasoning about non-pharmaceutical interventions. Conceived as decision-support tools, these simulations had to go well beyond standard epidemiological models in order to achieve relevance to the decisions that confronted university administrators. Specifically, they had to register human and environmental factors that traditional epidemiological factors neglect. These models needed to take account of buildings, classroom locations and sizes, class registration and attendance patterns, dormitory and dining arrangements, as well as the age and health vulnerability of students, faculty, and staff. They also needed to take account of social networks, which were presumed to define further avenues for viral spread.

I was drawn into these conversations at my own university and participated in many discussions about how to validate these models to the point that they could be used for decision support. Much of the data needed to validate such models was, in fact, available. But it was also private. In order to protect the privacy of this data, the team was cut to a tiny group of people with university permission to see even largely anonymized data and others were appointed to ensure that the data was properly anonymized and its use carefully monitored. That model did go on to function as a decision support tool, one in an arsenal of weapons that the university wielded with great skill in what became a leading example of a smart, timely, and effective response to university pandemic management.

This was impressive. I was gratified to witness computational social simulation used for something valuable and important so close to home. But I was also deeply troubled by twin ethical problems surrounding this situation. On the one hand, most universities do not have the built-in expertise to build reliable decision support tools, and the pandemic often poses a direct existential threat to those universities. In short, and ironically, the most vulnerable colleges and universities need decision-support tools more than the universities with the wherewithal to create them. On the other hand, the data needed to validate and calibrate these models is private and highly protected, meaning that models cannot be shared in their most useful forms.

To their credit, Kerr et al. (2020) created an open-source COVID-19 Agent-based Simulator (COVASIM). *"Covasim includes demographic information on age structure and population size; realistic transmission networks in different social layers, including households, schools, workplaces, and communities; age-specific disease outcomes; and intrahost viral dynamics, including viral-load-based transmissibility. Covasim also supports an extensive set of interventions, including non-pharmaceutical interventions, such as physical distancing, hygiene measures, and protective equipment; and testing interventions, such as symptomatic and asymptomatic testing, isolation, contact tracing, and quarantine. These interventions can incorporate the effects of delays, loss-to-follow-up, micro-targeting, and other factors."* But the specific human factors that matter most in universities, from social networks and class schedules to the realities of non-compliant parties and shared bathrooms in dorms, were not included. In fact, they really could not be included because the data needed to validate such matters was not publicly available.

A group of researchers at the Center for Mind and Culture, supported by additional experts from the working group of modeling and simulation of the COVID-19 Healthcare Coalition, ventured to surmount these ethical challenges surrounding the use of computational social simulation for decision support in university pandemic management. We created The Artificial University (TAU) using only *publicly available data*. TAU is validated in epidemiological respects like COVASIM but it was also responsive to human factors specific to university life, and those were validated using data that could be web-scraped without having to get special permission or violate privacy. These datasets gave us information on class schedules and structures, dorm and dining hall arrangements, bathroom sharing realities, social networks, commuting patterns, sports events, gym usage, and other university-specific concerns. Like COVASIM, TAU is open-source and has been downloaded scores of times. Users can overwrite the initialization data with their own data, if they have it, or they can use the scraped public data and just scale the university size to match their local population.

2.2 Ethical Questions

TAU effectively solves the twin ethical problems already mentioned and it has compelling results (Wildman et al. 2020). It has reached universities that need decision support but cannot afford to build their own simulations and it does not compromise privacy at any point. But this approach creates another ethical problem: a trade-off between validation and accessibility. Validation of TAU is weaker for a given university when only generic public datasets are used, rather than confidential data available within that university. A university can mitigate this problem by using private data in place of the public data in the out-of-the-box version of TAU that we distributed. But that in itself is an enormous amount of work and we suspect plenty of universities would happily use the built-in data, trusting that it is not so far from their private data that policy decision-making would be adversely impacted.

Our team debated the ethics of this validation-accessibility trade-off. We saw that we could mitigate the ethical problem by encouraging universities to employ their own private data but we were aware that this could be a self-exculpating evasion given that the universities who most need TAU's decision support are least likely to have the time and resources needed to fit new data to the simulation. This amounted to little more than a *caveat emptor* announcement, warning the user and then washing our hands of the entire validation vs. privacy problem. And yet it struck us as ethically far worse to withhold an open-source decision-support resource from colleges and universities that could never create their own just because it had been validated against public data.

We have not arrived at a decisive solution to this ethical conundrum. It might help to have a measure of the validation price paid for using public data rather than institution-specific data, but we do not have such a metric and doubt that one could be constructed given the diversity of institutions of higher education. In the meantime, our team feels more driven by the seeming injustice of the most vulnerable institutions with the greatest need for computational decision support being the least able to access it.

3 ETHICAL ISSUES IN COMPUTER MODELING AND SIMULATION WITH TRANSDISCIPLINARY TEAMS (SHULTS)

3.1 Use Case

Our second use case evaluates the application of the mutually escalating religious violence (MERV) model with transdisciplinary teams. Collaborating on the construction of computational models and the design of simulation experiments can be challenging, especially when the real-world target is exceptionally complex, or its interpretation is ethically charged and highly contested. This is certainly the case for many of the phenomenon our teams have attempted to model, such as religious conflict and minority integration (Shults et al. 2018a; Puga-Gonzalez et al. 2019). Building models of this sort raises a series of ethical issues, which I will discuss below in 3.2. First, I briefly describe the general approach we have developed for working with transdisciplinary teams when addressing policy-relevant societal challenges. This approach was set out in detail, and illustrated in several chapters, in the recent volume *Human Simulation: Perspectives, Insights, and Applications* (Diallo et al. 2019).

A more concise explanation of our approach was outlined in a recent article proposing its application in models oriented toward facilitating the achievement of the United Nations' Sustainable Development Goals (Shults and Wildman 2020). In that context we identified some of the "human factors" that play a role in the process of developing agent-based models (ABMs), especially when working with transdisciplinary teams composed of computer scientists and stakeholders such as subject matter experts, policy professionals, and change agents. Although the various steps in this process overlap, we can distinguish between six basic phases in this procedure:

- *Analyze Problem Situation*. The process of identifying and inviting stakeholders shapes the way in which the problem situation itself will be defined and analyzed. One of the challenges in this phase is balancing lines of convergence and lines of divergence among stakeholders. Too much convergence risks triggering groupthink and overly simplistic models; too much divergence risks triggering conflict and the collapse of the entire process. Here some of the ethically relevant human factors include desperation for change, resistance to change, and the roles of economic, political, ethical, and worldview alliances.
- *Create Problem Space*. Constructing the "problem space" of an ABM requires the identification of boundary conditions, leading causes of change, agent variables and social networks, and environmental parameters. Human factors that can raise ethical issues during this phase include cognitive biases that lead to misjudgments about the scope of the problem or its causal architecture.

- *Select a Specific Problem*. This phase involves specifying a particular problem within the problem space, selecting actors, variables, relationships, and parameters for the ABM, and deciding what would count as a solution. Here ethical issues emerge when human factors lead team members to focus on tractable problems instead of important ones, or to settle for unimaginative approaches to picturing possible solutions.
- *Design Solution Space*. Constructing the "solution space" involves identifying evaluation criteria for solutions, direct metrics matching data, and exploring (and possibly developing) novel derived metrics. As in the previous phase, here human factors can limit team creativity when it comes to imagining novel approaches with the potential to break new ground.
- *Critique and Iterate*. This phase involves the process of evaluating the experience and feel of model, determining whether the solution space is adequate and, if necessary, reframing the specific problem that had been selected in phase 3. One example of a salient human factor in this case is simple exhaustion, which can lead modelers and stakeholders to short-circuit the iteration process and settle for whatever insights have already been gained.

Although not explicitly a phase of the modeling itself, the process of the dissemination of the results also raises ethical issues. In the next section I will briefly address some of the ethical questions that can emerge during each of the overlapping phases as well as the dissemination process, in each case illustrating these issues in the context of the previously developed MERV model.

3.2 Ethical Questions

Analyzing the Problem Situation. In the case of the MERV model (Shults et al. 2018a), the core members of our research team were interested in understanding the conditions under which – and the mechanisms by which – mutually escalating anxiety and conflict between two religious groups occur. The extent to which "religion" drives conflict is contested among subject matter experts (SMEs) and we wanted to build a team that included individuals familiar with the debates as well as with the practical policy challenges that surround this issue. Monica Duffy Toft, a world leader in this field, was our main SME, and some of the other co-authors were relatively familiar with the relevant literature. Our team was highly convergent (sharing a similar theoretical approach), and the model would no doubt have benefited from adding divergent voices. Given the constraints in time and resources, we did our best to acknowledge our assumptions and attempt to "channel" divergent voices. This is simply a limitation of the model, and we made explicit our assumptions and choice of abstractions in the conclusion.

Creating Problem Space. Constructing the "problem space" of the MERV model required us to decide (among other things) on the variables, behaviors, and network interactions of the simulated agents. Recognizing the contestability of terms such as "religious" and even "anxiety" we analyzed and discussed relevant literatures and determined specific ways of operationalizing these concepts, and developed causal architectures that we believe represented some of the most salient insights from empirical research in social psychology and other relevant disciplines. We also discussed our own biases about the nature of religiosity, anxiety, and conflict, as well as the causal relations among these variables. Although such discussions do not protect against the influence of our biases within the model, at least we attempted to make them as explicit as we could so that others can challenge them and adapt the model in different directions to explore other hypotheses based on other theories and empirical data.

Selecting a Specific Problem. While intergroup conflict in general is an interesting and important topic, we selected the specific problem of the causes of mutually escalating religious anxiety. That is, what parameters would lead members of the two religious groups in our model to pass thresholds (taken as a proxy for conflict) that would lead to series of mutually reactive expressions of anxiety? Decisions about the causal architecture were informed by terror management theory, social identity theory, and identity fusion theory. What would count as a solution? The discovery of the parameters of the model in which the mutual escalation of conflict-generating xenophobic anxiety would emerge at the population level. We considered the more tractable problem of discovering the cause of increased anxiety in general but decided to aim to solve this more complex problem.

Designing Solution Space. How would we know that we had found such a solution? In evaluating criteria for this solution, we explored a wide variety of data sets and ended up focusing on data from the troubles in Northern Ireland, which lasted 30 years, and the Gujarat riots in India, which lasted about 3 days. In both cases, there was significant and mutual escalation of violence between religious groups (Roman Catholic and Protestant in the first case, Hindu and Muslim in the second case). A good solution in the model would match what we see in these real-world situations. The most common solution we found in the simulation experiments did in fact match those situations (in relation to population distribution, and the extent of social and contagion threats in the environment). This provided some external validity to the model, but it does not pretend to be predictive.

Critique and Iteration. In order to increase the internal validity of the model, we engaged in several internal code reviews, used established libraries whenever possible, and analyzed the output of 20,000 model executions when describing our results. We spent a couple of years on this model, and even when exhausted, kept encouraging each other to continue the iteration process until we were able to generate insights that shed light on the phenomenon by implementing some of the relevant theories based on empirical research on religious conflict.

The MERV model has gained significant attention in the press, leading to interviews with BBC and Der Spiegel and articles in dozens of international online news outlets including The New Scientist and The Atlantic. As with all science, once the research is in the public domain the scientists lose some control over its effects. In interviews and podcasts, we did our best to emphasize the limits of the model, but several outlets sensationalized our findings while others misrepresented and downplayed them. Another relevant ethical issue is that the construction and dissemination of this model raises a challenge that is shared by many other technologies (e.g., nuclear power, genetic engineering): it could be used for “evil” as well as “good.” In this case, a “good” use (in our view) would be finding ways to prevent religious conflict. However, it is possible that people with other motives and ethical assumptions would use the insights from MERV to promote religious conflict. This highlights the importance of considering the potential ethical issues that will emerge once a model has seen the light of day and is in the public domain.

4 “FEET OF CLAY” VALIDATION – THE NEED TO VERIFY VALIDITY (TOLK)

Interestingly enough, within the simulationists’ community, the question for truth – *veritas* – is applied to transformation accuracy, while the representational and behavioral accuracy requires strength – *validity*. In the context of model validity, this is generally understood that the model is grounded in strong foundations. Traditionally, empirical data were considered to be the strongest foundation, but in domains other than physics-based models, empirical data is not always accepted as the best way to represent truth.

In his essay on truth in simulation, Schmid (2005) evaluates the applicability of accepted philosophical definitions of truth relevant to simulation as a tool of constructivism, and he identifies correspondence, coherence, and consensus theory. *Correspondence* theory of truth assigns truth values to simulation based on their correspondence with a fact of reality, taking a positivistic and empirical standpoint: Truth is what can be empirically observed, but in postmodern discipline, this is no longer accepted as the best way. *Coherence* theory of truth translates these ideas into constructivism. If the simulation belongs in a set of members of a coherent system of beliefs, then it is considered to be true among these members: Truth is what is accepted based on rationalism by the group. *Consensus* theory assigns truth interpretations to something depending on whether it is rationally acceptable under ideal or optimal conditions. These conditions are agreed upon in the participating group: Truth is what is commonly believed within the group. The latter is also a justified means to show validity: if a model is shown to correspond with a model already shown and accepted to be valid in the community of interest, it is assumed to be valid as well.

If we apply these ideas of consensus with an accepted model or data set to show that our models and parameters are valid, we have to ensure two things: that our model really matches to the one we use as our reference and the parameters are fitting for our purposes, and that the referenced model or presented data set indeed are valid themselves. In particular when we are very passionate about a topic, in cases where moral and epistemological considerations are deeply intertwined, it is human nature to cherry-pick the results and data that support the current world view (Shermer 2017). We therefore have to be very careful that we are most critical to check the validity of data sets and models we agree with.

4.1 Use Cases

Two use cases are presented to show the need for the critical check of the validity of data sets, one out of the domain of the opioid epidemic, the other from the recent COVID-19 pandemic.

The investigative reporter Quinones (2015) conducted intensive research on the rise of the opioid epidemic within the United States. Within his research, he points to what should just have been an anecdotal side story, but what became one of the scholastic use cases for insufficient validation principles with catastrophic consequences. Quinones describes that Dr. Hershel Jick collected data on drugs used in hospitals and their effects since the early 1960s at the Boston University School of Medicine. He heavily relied on the skills of his assistants for computer access and database queries, as he never used computers for himself. In 1979, he was curious about the number of patients in the database who developed an addiction after being treated with narcotics. Based on the data extracted by his assistant Jane Porter, only four patients of the almost 12,000 patient records in the database became addicted. He typed this information up to share it with colleagues and submitted it as a letter to the New England Journal of Medicine (Porter and Jick 1980). The short letter did not capture any details, had no verifiable sources, and only stated the pure numbers. It did not mention the age of the patients, which were mostly elderly, nor any period of observation. It is also not known how the assistant retrieved the data and validated that the four cases indeed are the only ones. But as this is simply a letter to the editor, such shortcomings can be forgiven. However, the letter was not treated as such an anecdotal database access with an interesting, but hardly validated observation. Instead, as observed by Leung et al. (2017), 608 articles are referencing this one-paragraph letter as a justification for the validity of the assumption that opioid based narcotics are not leading to addiction. The numbers of citations increased significantly after the introduction of OxyContin, as the pharmaceutical industry introduced this new pain killer to hospitals and doctors. 439 papers cite the letter as evidence that addictions are rare. One of the few details in the letter by Porter and Jick, namely that the patients were hospitalized, is overlooked by 491 of the referencing papers. In other words, a major medical development, namely the tremendous increase of opioid-based pain treatment, was based on the pedigree of a one-paragraph letter that was not even evaluated properly by those who referenced it, likely because the title promised the evidence for which those authors were looking. As those papers were referenced themselves, a set of legions of papers published that the opioid use to treat pain is harmless. It was not harmless: according to CDC data on opioid misuse, between 2000 and 2015, more than 180,000 deaths from prescription opioids are recorded.

The second use case in this section is based on observations in (Winsberg, Brennan and Surprenant 2020) which critices the use simulation results in the context of the COVID-19 pandemic. Winsberg is very experienced in the use of computer models to support scientific work (Winsberg 2010), so his critical look at the use of computer models to justify the interventions by the US and UK Government based on model predictions should be noted. He is in particular critical on how the model of the Imperial College in London (ICL) has been applied. The criticism is not against the model itself, but the lack of rigor applied before recommendations were given. As Winsberg and colleagues observe: *"When epidemiologists model an emerging epidemic, data are sparse. In constructing their models to make forecasts, they have myriad methodological decisions to make, many of which are unconstrained by data or existing background knowledge."* This observation is equal to the insights published in (Tolk, Glazner and Ungerleider 2020), where the recommendation was to focus to use models and simulation to understand what *may* happen, but never to promise to model what *will* happen. But such warnings were not applied at the early time. Again, the model itself is not criticized, but the way it was used without availability of critical data, and how the results were used later to validate other work. Data was sparse, and the scientific insights into COVID-19 were limited, but nonetheless very specific values had to be chosen for important parameters, such as death rate, hospitalization rate, and rate of admittance to intensive care, as well as contact rates and the probability of infection at work, school, or at home, just to name a few. Such uncertainty in parameters is usually addressed by extensive sensitivity analysis over the uncertain parameters, often even involving several model configurations and structures (Marchau et al. 2019), but as a single run of the ICL model requires approximately 20,000 processor hours, such a massive parameter sweep was not possible. As a result, best guesses were used by subject matter experts to capture parameters unique to an unknown epidemic. Like in the first use case, the results became the validation yard stick for follow-on activities, without the critical look at the foundation of the original data and their use within the model. Simulation results that were in alignment with the early predictions were trusted, while alternative simulation results were met with significant skepticism, which should have been applied to all simulation results, not limited to those that did not support the preference worldview.

4.2 Ethical Questions

The use cases described above are an application example for the section 2 on professional competence of the *Code of Professional Ethics for Simulationists* (Ören et al. 2002). We will look into a subset of this section of particular interest to our use cases in the next paragraphs.

Provide full disclosure of system design assumptions and known limitations and problems to authorized parties. The available publications addressing the use of modeling and simulation to address the opioid crises as well as the COVID-19 pandemic are sparse on describing assumptions and constraints. Part of this is the accepted structure of journal papers (introduction, materials and methods, results, and discussions) which do not yet reflect simulation-based experiments too well, but for sure more transparency is needed. To provide a good description of assumptions and constraints of a simulation is hardly possible within the current practice of many journals. The work described in (Uhrmacher et al. 2016) may provide some help, but how to disclose assumptions and limitations in the language of the user of data and models remains a challenge. Nonetheless, we cannot simply publish simulation results and recommendations without describing how we accomplish them.

Caution against acceptance of modelling and simulation results when there is insufficient evidence of thorough V&V. This is actually a very challenging request for ethical behavior, in particular when the time for action is now, and alternative providers of recommendations may not have the same rigor underlying their recommendations. Nonetheless, providing evidence based on shaky foundations is wrong, although understandable, in particular when there is a strong personal moral connection to the problem. But validation cannot be a personal preference, it must be a professional principle, providing constructive criticism leading to better recommendations.

Assure thorough and unbiased interpretations and evaluations of the results of modelling and simulation studies. The model is the reality of the simulation. Whatever is within the model can influence the simulation, but there is no magical emergence of relations in a simulation that are not captured in the model. It may be that hidden information is discovered, but only within the model. The epistemological and hermeneutical challenges have been described in more detail in (Tolk et al. 2018).

In summary, it is not ethically justifiable to simply point to another publication for validation without validating the applicability and rigor of this work itself. In the time of search tools like Google scholar, Mendeley, and the like it is tempting to quickly scan the publication landscape for publications that seem to support one’s case, but caution is not only in order, it is ethically mandated. In particular when data is sparse, the solution space is highly non-linear and complex, and experts do not yet agree on a broadly accepted theory, we cannot assume that data and models can easily serve for validation on the basis of consensus. Otherwise, insufficient rigor can quickly become the basis for far reaching recommendations to decision makers based on models with “feet of clay.” Our data, models, and simulations have real life consequences and have to be treated accordingly.

5 CULTURAL EVOLUTION CHALLENGES (LANE)

Cultural evolution, in general, is the study of cultural changes over time framed within a framework of selection, typically by framing cultural changes as Darwinian processes. In recent years, research from cultural evolution has been increasingly embraced by researchers, as seen by an increase in prevalence of publications on the topic: according to the dimensions dataset (Digital Science 2018), the number of publications mentioning cultural evolution has more than doubled from 75,077 in 2012 to 155,765 in 2020. In the past, many scholars have raised questions concerning how one can apply evolutionary theory (either directly or as an analogy to biological evolution) to the study of culture, given how difficult it is to define culture. Unlike the many examples from physics and engineering in the modeling and simulation literature, and unlike the genetic material of DNA, culture is not a natural kind that can be put on a table, weighted, and measured. As such, many scientific measures and theories are debatably inapplicable to creating the links between a model of culture and the real-world subject of a model of cultural change. For example, the very question of what constitutes "Culture" is as thorny an issue as ever, with different schools and theories choosing to focus on different aspects of those human actions and artefacts that we heuristically feel is part of something we can safely call culture. As such, many models of culture risk reflecting ideological biases more than reality if a simulation has no viable, testable, relationship between its cultural simulacra and the real-world observations it attempts to address.

These issues in validation can be seen directly in the study of cultural evolution, wherein the concept of validation in the sense that it is used in the modeling and simulation world is largely non-existent. A quick search in the Dimensions publication database suggests that in 2020, 92% of the publications that mention cultural evolution have 0 mention of the terms "simulation," "verification," and "validation" (Digital Science 2018). In those rare instances where validation is attempted in the seminal literature on cultural evolution, it is typically only face validation, or analogical ties to historical observations or, in even more rare cases, empirical observations. The pattern in the literature on cultural evolution, and the models on which it is based is that face validation, wherein the outputs of the model being taken as confirmation of the theory is not so much validation as it is an epistemological tautology where confirmation is assumed because the model confirms the theory confirms the model, such as described in (Tolk 2017).

Without proper validation techniques in the field at large, poorly validated models can become cannon in the literature, and the assumption on which they are built can become entrenched in the field and not questioned later. This can result in poorly validated, unvalidated, or (as discussed in the next section) arguably refuted models, that nevertheless become the basis for further theorizing and additional models.

5.1 Use Case

The use case in this section emphasizes the need for V&V of models when these are being used to generate quasi-empirical support for new theories which may remain perceived to be correct even if the underlying model assumptions are falsified, or at least deeply questioned.

In 2004, the Journal American Antiquity published an article titled "Demography and Cultural Evolution: How Adaptive Cultural Processes Can Produce Maladaptive Losses-The Tasmanian Case" (Henrich 2004). In this article, a model was presented and the conclusion of the model, after having undergone basic face validation (in relation to a narrative overview of historical data), was that adaptive cultural processes can produce maladaptive losses in cultural information and that this is dependent on group size. Specifically, it claims that the model *"precisely specifies the conditions under which particular skills will enter a regime of maladaptive deterioration until reaching a new less-well-adapted equilibrium"* (Henrich 2004, p. 209). This study has gone on to be cited over 1000 times (according to Google scholar), which in the study of culture, is well above any conceivable average.

After the publication of the article, another article, "Tasmanian Knowledge And Skill: Maladaptive Imitation Or Adequate Technology?" (Read 2006) was published discussing what could be considered critical refutations of the original model, citing, among other issues, that the model was not consistent with the complexity of tools used by hunter-gatherers, that the model was not consistent with the data from

Tasmania on the subject during the time period, and—perhaps most damningly—that the model required unrealistic parameters for any maladaptation to occur. The article by Read put forward a new model (based on cost-benefit analysis rather than Darwinian evolution) that suggested that the loss of skills was more related to the changes in resource procurements strategies and technological changes than a shortage of skilled individuals due to any decreases in population size.

In response to these allegations, the initial author published an additional article (Henrich 2006) attempting to refute Read's response on the basis that the initial article was mischaracterized and that the data presented in response had empirical errors, at which point the first actual validation of the initial model by the author appeared in print.

This back and forth was continued with a response by Read (2011), who focused on demonstrated that there were, in fact, no empirical errors on his part by analyzing the relevant data, but on the part of Henrich in an additional publication. Most critically, Reads analysis of the data appears to show quite clearly that variation in population size is independent of variation in tool complexity. In yet an additional paper, Read (2012) puts the model through further validation, discussing at length how many of the initial model's (Henrich 2004) critical assumptions are invalid.

By the time that Read had written the last response, there were already at least 18 peer reviewed papers published citing Henrich's original model, however, these publications appear to be ignorant, or negligent, or Read's critique, despite it being published in the same journal, and garnering a response from Henrich directly. This pattern has only grown, as the initial study, cited over 1000 times, with most citations coming after Read's responses were published, has far outpaced Read's critique, which has only garnered 126 citations according to Google Scholar. Henrich's reply to Read currently has at least 64 citations (according to Google Scholar).

More recently, an additional paper discussing the issues in evolutionary models of cultural complexity and population size, the authors demonstrated that models are flawed in their assumptions and their predictions are not supported by the available data (Vaesen et al. 2016a). A response was issued to this paper by Henrich et al. reiterating the earlier critiques leveled against Read, without citing the multi-paper exchange with Read directly in their text, instead citing it only in an online appendix (Henrich et al. 2016). As one might expect, in response to this, Vaesen et al. (2016b) responded to Henrich, showing, as Read did before, that most of the responses misrepresented their critiques of what had become—by this point—known as *"the Tasmanian effect"* (and thus, Henrich et al. attacked straw men) and that overall, none of the points of Henrich et al. contradicted the initial arguments from Vaesen et al., and they conclude that *"there is no reason to think that population size explains any, let alone all, changes in cultural complexity in the past"* (Vaesen et al. 2016b, p. E6726).

This leaves the idea that population size causes cultural complexity on spurious grounds at best. While one network of researchers has stated that their models demonstrate these effects, other networks of anthropologists, archaeologists and historians with varying backgrounds in modeling and simulation have been unable to find evidence for this, validate the initial models, or find supporting evidence for the parameters of the model. Such findings are calling the utility and the validity of the model into question. Nevertheless, this keystone of the cultural evolution literature, being cited in Henrich's bestselling books, among other places where it has been uncritically reiterated without a full depiction of the controversy of the models and is still widely utilized in the field. All this, despite new data calling into question the basis of its memetic approach and empirical demonstrations that the idea that cultural information is transferred in such a way is itself problematic and therefore the model may be an oversimplification in that assumption as well (Scott-Phillips); although in fairness, Henrich and his network have argued that the assumption could be relaxed in theory in additional models (to date unvalidated: Henrich et al. 2008). The importance of this debate however should also be understood as quite serious as leaders in cultural evolution propose that this neo-social Darwinism should be the basis of economic and public policy (Gowdy et al. 2013; Wilson et al. 2013) —despite its core models going largely unvalidated and many of its claims being noted as "faith" in the theory (Mulder 2019).

Ultimately, this dispute appears to reveal a more subtle issue of modeling and simulation in the humanities and social sciences, which is a confusion—or ignorance—of the difference between validation and verification. In the humanities and social sciences, the theory that one employs creates the framework for understanding some phenomena. Often, explanation is not even attempted, and understanding is considered sufficient. This is exemplified in what we can call the first "Durkheimian Fallacy"—that the social level of explanation is all that is needed to explain the social, the second "Durkheimian Fallacy" being that we can use tribal cultures as a lens into our evolutionary past. In this research paradigm, the theory that one proposes, or focuses on, is critical to career advancement, and if a theory is considered falsified or not useful, then it is a threat to a career. This disincentivizes attempts to falsify. When employing modeling and simulation as a method, one can similarly protect theoretical hegemony by promoting model verification, assessing that the model is doing what it is expected to, instead of model validation, empirically assessing that the model is an accurate-enough representation of the real world.

5.2 Ethical Questions

The use case presented in 5.1 raises several ethical questions. First, to what extent does a scholar have the imperative to include within future work some note or flag about a concern that has been raised in the literature, or elsewhere by an informed stakeholder? To an extent, the practice of software development could provide an interesting solution. If we consider "questions" (i.e., challenges or possible flaws) concerning the validly of a model, bug tracking (such as submitting fix tickets through public repositories such as GitHub) could provide a forum for continuous engagement and validation of a model after its initial release and also provides clear tracking, at the source, of additional concerns raised by stakeholders; the drawback being that as this would not be something necessarily published in an academic paper, it would not overcome any publication biases that may occur by researchers who neglect, or are ignorant of, noted issues that have been raised.

Second, to what extent should models that confirm a theory through face validation, but fail to be sufficiently validated by real world data or further validation, be considered appropriate for policy decisions? This question cuts to the heart of a great deal of the current trend in cultural evolution. Many of the field's most cited authors, such as David Sloan Wilson, have publicly suggested that Social Darwinism, as a form of cultural evolutionism, be utilized for policy and have (at least) attempted to engage with politicians at different levels to influence policies. On the one hand, models (as we see in the other sections of this paper) can have positive effects on policy making and can provide use in complex decision making. However, in light of the poorly defined abstraction within models of cultural evolution (defining culture, over-reliance on "meme theory", concerns of validation and parameterization), is it worth the risk to implement a model that is, without validation, little more than an ideological reflection as a "scientific" basis for policy? If we accept that a model is a theory, and a model that is unvalidated is an untested theory, implementing poorly-validated models of cultural evolution for social and economic policy is little more than a complex justification for implementing pre-conceived ideological positions under the guise of science, when in fact no scientific method is required, the model builder is likely misleading the general public, who cannot be expected to be fully engaged with questions of computer model validation, by suggesting that a scientific conclusion has been reached that could guide policy, when in fact, that is not the case. To put it bluntly, utilizing unvalidated computer models for policy is no better than arguing one's own ideology (flawed as it may be), it just suffers from greater ethical suspicion because one is attempting to appropriate science to support their argument when in fact one is generally pushing the foregone conclusions of their own ideology, writ in code.

In the case of cultural evolution however, this then has an additional layer, which is adding the guise of scientific foundations to what is a new form of Social Darwinism. In recent years, key proponents have suggested that Social Darwinism can be a good thing. However, when we look at aspects of human culture such as ritual and many cultural beliefs that give different cultural groups their beautiful and unique features, there is no utility to the belief or behavior. Ritual, by many definitions in the literature, is a goal-demoted behavior, meaning there is no logical connection between the natural outcome of the action and the action itself. As such, how could one define the utility function required to argue for the selection of such a behavior as something that would be an adaptation for that cultural form, if not by lensing one's own preconceived notion of what is good into the model? If this approach is extrapolated to the level of policy implementation, we risk suppressing cultures that are not part of the cultural hegemony, as those who are in power could just protect their power by using arguments for selection to address what they could allege (but not need to prove) that some cultural form is "maladaptive", leading ultimately to the extinguishing of culture on the basis of the arguments of social Darwinism. Whereas in the early 1900s, the implementation of Social Darwinism led to several Eugenics programs at state and federal levels, this "new social Darwinism" could lead "cultural eugenics" if not checked—it is worth noting that both social Darwinism, cultural evolution, and eugenics all publicly proport to be for the betterment of society in the policy arena. This is not to argue that models of cultural change are not valuable in making decisions and to inform policy, rather, that without putting validation at the fore (and understanding the difference between validation and verification), models are used to justify possibly oppressive or dangerous policy decisions, not to assess complex issues. The critical ethical question that cultural evolution must empirically demonstrate before its proponents should be allowed to engage in policy formation is: how is cultural evolution circumventing the problems and ethical issues of social Darwinism and how can we ensure that cultural beliefs and practices will be protected from destruction because they do not fit with a model's ideological assumptions?

6 SUMMARY AND DISCUSSIONS

Based on our use cases and ethical discussions, we suggest a call to action for extending our understanding of V&V. First, as the application of modeling and simulation is increasingly used to drive life-changing social and political decisions, V&V is more important than ever. As the philosophical understanding and definitions of truth differ in the social and technical components of socio-technical systems, we have to broaden our understanding of V&V as well to address resulting challenges. And finally, V&V must be rooted in a metaethical framework that helps to address the ethical challenges observed.

Our society is facing multiple challenges calling for social and political decisions that may have far-reaching consequences. An obvious recent example of the importance of models and simulations to guide decision makers is the COVID-19 pandemic, where public-health recommendations and mandates were often based on model predictions of future development with and without certain non-pharmaceutical and other interventions. Examples of other pressing challenges are the search for social justice and equality, climate change and its implications, distributive economic justice—and there are many other topics demanding political and social action. Simulation can and will provide computational decision support, extending its range well into social domains (Suarez and Demerath 2019). This requires us to rethink how and maybe even why we conduct V&V, and how we may have to change modeling and simulation curriculums to address this. We certainly have to be vocal as a community to ensure that decision makers clearly understand the assumptions and constraints their decisions are based on, be it the validity foundation for the model and the data, the underlying philosophical ideas, or the application constraints.

To do this, we need to better understand how social theory and humanities handle truth and validity, and how we can incorporate their views into V&V efforts. Naturally, one issue here arises from those theories in the humanities and social sciences that operate in theoretical spaces that do not accept empirical data as a source of truth. In those cases, validation is likely not able to address critical issues, as the epistemological framework of the theory does not require the research to accept that real-world empirical data has value in the same way that experimental and observational science does. In particular, computational simulations in fields or theories operating with certain postmodern epistemological frameworks may have no use for validation, even if verification retains a role. In certain other postmodern epistemological frameworks, even verification would be out of reach, because verification assumes that theoretical and logical consistency are valued in ways that some postmodern epistemologies reject.

In instances where both verification and empirically grounded validation are accepted, truth claims can be validated through empirical data, and models can be verified using the best available data while simultaneously providing a platform for testing the assumptions of the theory being modeled. Here, these challenges may help to create greater theoretical clarity and provide tangible results that can allow humanities scholars and social scientists to engage more fruitfully on key topics within their domain, including social problems. This applies not only to modeling and simulation, but generally to the gathering of data that is useful for the V&V of a model as well. The lessons learned may therefore be of interest to the Artificial Intelligence community in general, and the Machine Learning community particularly, as well, as the availability of valid and good data is essential for them as well. The development and release of such a verified model can make it a target of validation for other researchers to challenge. A much more intensive discussion with the humanities is needed to address such issues, as we need to get a better understanding of the social components of the socio-technical systems that we want to study. We are only in the beginning of this process.

As noted in the introduction, we believe that ethical challenges surrounding V&V issues require more careful attention within the M&S community. It is not sufficient to limit discussions about ethics to professional behavior or the ways in which technology ought to be engaged by users. We also need to frame the entire process of model construction and dissemination, including verification and validation, within a broader “meta-ethical” discussion of the values guiding our work (Shults and Wildman 2019). Such discussions help bring ethical assumptions to the surface, in relation both to presuppositions within the model architecture and the purpose of the simulation experiments we design. All this may well require a revisioning of the codes of ethics that inform our profession.

Our deliberations here are part of an ongoing discussion, see (Shults et al. 2018b). We hope that the observations made in the use cases and the ethical questions identified will provide an initial foundation for further debates about the ethical implications of modeling and simulation.

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