Aspects of Modeling Human Behavior in Agent-Based Social Simulation – What Can We Learn from the COVID-19 Pandemic?

Emil Johansson[1,2](✉), Fabian Lorig[1,2], and Paul Davidsson[1,2]

[1] Department of Computer Science and Media Technology, Malmö University, Sweden
[2] Internet of Things and People Research Center, Malmö University, Sweden
{emil.johansson,fabian.lorig,paul.davidsson}@mau.se

Abstract. Proper modeling of human behavior is crucial when developing agent-based models to investigate the effects of policies, such as the potential consequences of interventions during a pandemic. It is, however, unclear, how sophisticated and versatile behavior models need to be for being considered suitable to support policy making. The goal of this paper is to identify recommendations and suggestions on how human behavior should be modeled in ABSS as well as to investigate to what extent these requirements are actually followed by models explicitly developed for policy making. By analyzing the literature, we identify seven relevant aspects of human behavior for consideration in ABSS. Based on these aspects, we review how sophisticated agent behavior is modeled in ABSS of COVID-19 interventions. This is to investigate the capabilities and limitations of these models to facilitate decision making and to provide policy advice. We particularly focus on models that were published soon after the start of the pandemic as this is when policy makers needed the support provided by ABSS the most. It was found that agent behavior in the models often was not sufficiently sophisticated for investigating the effects of interventions, especially in regard to norm compliance, agent deliberation, and interventions' affective effects on individuals. We argue that ABSS models need a higher level of descriptiveness than what is present in most of the studied early COVID-19 models to be of help to policymakers.

1 Introduction

Human behavior is a crucial part of understanding complex social phenomena, such as the transmission of COVID-19. Accordingly, considering human behavior is of great importance when developing interventions (policies) to counter a pandemic. It is the behavior of individuals and groups that generates the social dynamics that policymakers aim to govern. Hence, only by taking into account individuals' compliance to interventions can their effects on the spreading of the disease be truly understood. Only through acknowledging the heterogeneity in individuals' behavior can the impact of super-spreaders be explained. And only by considering how people adapt their behavior can the effects, the success, and the consequences of different policies and recommendations be investigated to identify the most suitable and least restrictive measures. All these aspects can be captured in Agent-Based Social Simulation (ABSS) models, making them well suited for modeling complex social phenomena like epidemics [9]. In the early stages of the COVID-19 pandemic, a great number of ABSS models was published to study the effects of different interventions [18]. However, when used for this purpose, it is crucial that models are developed to capture the complex behavioral and social mechanisms at play to be able to investigate the effects of policies [28].

Adequately modeling human behavior is one of the main challenges of ABSS. However, using ABSS to support policy-making during a crisis places entirely new requirements on the design of these models, something which was brought to light by the COVID-19 pandemic. On the one hand, the need to supply decision-makers with information as quickly as possible puts a significant time pressure on the development of the models. On the other hand, the initial lack of data and information on both the crisis itself (for instance the disease transmission probability in the case of COVID-19) and individuals' behavioral response to it and to interventions makes model development and calibration difficult. Still, tackling these challenges rather than resorting to over-simplified models is crucial if ABSS is to render trustworthy support for policy-making.

For modelers, it is challenging to determine how to model human behavior to support policy making. There are no general standards or guidelines on how sophisticated behavior models need to be for different purposes. Still, there exist different recommendations and suggestions on individual aspects of human behavior that might be relevant to include in ABSS. But even though these requirements exist, it is unclear if and to what extent they are actually considered and integrated by models explicitly developed for the purpose of analyzing policy interventions. Hence, as a first step towards developing useful and informative ABSS for supporting policy making, it is necessary to identify and consolidate these different recommendations.

The goal of this paper is analyze how human behavior should be modeled in ABSS for policy making as well as to investigate to what extent existing models developed for the purpose of supporting policy making actually fulfil these requirements. To this end, we first analyze and discuss the body of knowledge of how human behavior should be modeled in ABSS to allow for supporting policy making. From the literature, we identify relevant aspects of human behavior that should be considered when developing ABSS of policy interventions. Based on this, we then investigate how sophisticated agent behavior is modelled in ABSS that were particularly developed for providing policy advice. We use the example of COVID-19, where a great number of models for analyzing interventions was published. We particularly focus on early models published shortly after the first outbreak as this is when policy makers needed the support provided by ABSS the most. For this purpose, we use the corpus of ABSS identified by Lorig et al. [18] and focus on the studies with more elaborate behavioral models. By analyzing deviations between how human behavior should be modeled and actually is modelled, we want to better understand what support modellers need to facilitate policy making.

The paper is structured as follows: Section 2 provides an overview of related work on the modeling of human behavior in ABSS. In Section 3, relevant aspects of agent behavior are presented. Section 4 presents the results of the model review and Section 5 discusses the results and implications for future studies.

2 Modeling Human Behavior in ABSS

There exists no general advice or guidelines on how human behavior should be modeled in ABSS, especially when intended for policy support. Still, different researchers have identified relevant aspects of human behavior that. This section present relevant literature on modeling agent behavior in ABSS models.

Balke & Gilbert [5] discuss what models of human decision making are required for different research questions. They present and analyze different architectures for agent behavior and identify five dimensions for comparison: cognitive, affective, social, norm consideration, and learning. An [2] reviews and compares models of human decision-making used in coupled human and natural systems (CHANS). She distinguishes between empirically based and processes-based approaches and notes a lack of protocols for modeling human decisions. Macal [19] proposes four consecutive agent properties: individuality, behaviours, interactions, and adaptability, and argues which properties are required for different purposes. According to Macal, social simulation require individual heterogeneous agents with autonomous dynamic behavior and interaction between other agents and the environment. The importance of appropriate cognitive architectures for understanding collective human behavior has also been outlined by Sun [29]. The author proposes a hierarchy of four levels of analysis, that allows for different types of analyses depending on the level of abstraction of the cognitive models.

The ODD protocol [10] was developed as a standard of how to communicate agent-based models. The protocol has been extended by Müller et al. (ODD+D) to also describe human decisions in agent-based models [20]. Guiding questions include whether agents are heterogeneous in their decision-making, whether individual learning is included, and whether norms play a role in the decision process. Schlüter et al. [25] propose the MoHuB framework for mapping different behavioral models. This is aimed to help compare and communicate different models of human behavior.

Surveys on how human behavior is modeled have also been conducted for specific fields. Groeneveld et al. [11] present a systematic review on how human decision-making is modeled in agent-based land use change models. Klabunde et al. [17] analyze decision-making rules in agent-based models of human migration. Huber et al. [14] review agent-based models of the European agricultural sector, focusing on how decision-making was implemented. Finally, Groff et al. [12] investigate agent-based models of urban crime, including offender decision-making modeling.

The approaches presented in this section underline the importance of certain aspects of agent behavior depending on the purpose of the simulation. Yet, they do not provide comprehensive support for modellers to determine which aspects are relevant for a particular study or use case.

3 Aspects of Agent Behavior

Based on the works presented in Section 2, we can identify seven aspects of agent behavior that seem necessary for capturing more complex human behavior in social simulation models. We argue that any exclusion of one or more of these aspects should be justified by the modeler. To define and illustrate these aspects, we use the modeling of the COVID-19 pandemic as an example of application. For some of the aspects and for this specific use case, we also identify some different sub-aspects that further divide and differentiate these. This list of sub-aspects is not exhaustive for all modeling of human behavior, but aims to illustrate how the aspects should be understood for different applications. The seven aspects are described below.

3.1 Attribute Dependence

Do the individual attributes of agents affect their behavior? Attributes are defined here as individual parameters that vary between agents but usually stay constant during the simulation, and are thus closely linked to the heterogeneity of the population. A larger number of agent attributes generally means more heterogeneous agents. Attributes might include agent age, gender, workplace, body mass index, car ownership or family ties, as well as individual preferences or personalities. Of course, what differences between individuals are deemed as relevant for the currently simulated system will of course vary greatly between areas of application. Attribute-dependent behavior thus means that agents behave inherently differently.

It is obvious that individuals or groups with different behaviors are essential for modeling some COVID-19 interventions. School or workplace closure models, for instance, need to differentiate between agents who attend these facilities and those who do not. Heterogeneity in behavior has impact far beyond the effects of these particular interventions [24]. From understanding the role of children in the infectious spread to understanding the phenomenon of super-spreaders, descriptive analysis of interventions requires a heterogeneous population with heterogeneous behavior. In addition, epidemics and non-pharmaceutical interventions affect different individuals and groups asymmetrically, for instance between genders [16] and income levels [30]. It is important to consider the most influential attributes that are assumed to affect the consequences of an intervention.

3.2 State Dependence

Do the agents' internal states affect their behavior? The *state* of an agent is defined by the values of its internal parameters (attributes), or a subset of these, and usually changes during the course of the simulation. Agent behavior is usually directly related to an agent's state, which is why the diversity of agent behavior depends on the number of possible states an agent can have [19]. State-dependent behavior, thus, means that the same agent placed in the same environment at different times could make different decisions due to differences in parameter values, even beyond potential randomness in the decision-making process.

We identify two sub-aspects relevant to epidemiological modeling: *Disease State Dependence* and *Affective Dependence*. **Disease State Dependence** refers to that agents' behavior is affected by their current disease state. The simulation of different isolation strategies explicitly requires that infected individuals behave differently than those who are healthy, but even beyond this, agents changing their behavior with their disease state is a fairly basal requirement of realism in epidemiological models. A severely ill individual will not behave in the same manner as had they been healthy, regardless of the implemented interventions. Similarly, most negative effects of interventions cannot be studied if agents ignore their own disease state.

Affective Dependence refers to the existence of some representation of emotions or affective state, and that this can affect an agent's behavior. One of the main drawback of several interventions is what impact they have on individuals' mental health. The risk of such effects and their influence on compliance and other behavioral responses was identified early during the COVID-19 pandemic [8], and these fears appear to have been justified [23]. Thus, taking such effects into account is crucial for a deeper understanding of the effects of interventions.

3.3 Uncertainty Dependence

Does the agents' lack of information affect their behavior? Here, *Uncertainty* refers to agents not fully knowing the state of all other agents and the world. As argued by Simon [27], the human mind cannot be understood or predicted unless it is known what information it has. A model which does not take this into account is making very optimistic assumptions on the rationality of agents. Few simulations have agents take into account *everything* in the model when making their decisions, meaning there already exists some level of implicit information imperfection. More interesting to look at is what information is explicitly hidden from agents, and what false or uncertain information they might receive.

We identify one important source of uncertainty-dependent behavior in epidemiological modeling in the existence of **Other Diseases**. While these might not explicitly influence the spread of the studied epidemic, they will affect the number of quarantined individuals. One common policy during the COVID-19 epidemic has been to ask (or force) individuals to stay at home if they or a household member of theirs are feeling ill, before a negative COVID test result has been received. A model which does not include the possibility of showing symptoms without having COVID then risks to gravely underestimate the number of isolated individuals and thus the economical or affective effects of such an intervention.

3.4 Context Dependence

Does the agents' context affect their behavior? Context refers to all external factors that could guide an agent's behavior, for instance, its surrounding environment, other agents, or the current time. These would not be implemented as individual agent parameters, but in a global manner. Insight into which of these external factors affect the decision-making of agents is crucial for explaining their actions.

Two types of context dependence relevant to epidemiological modeling are identified. **Social Context Dependence** refers to the agents' behavior being affected by other agents. Models studying household isolation or test-and-tracing strategies require this sort of dependence, as these interventions consist of changing an agent's behavior based on the disease state of others. Furthermore, social influence plays an important role in the decisions individuals take, and can for instance positively or negatively affect individual's willingness to comply with interventions [21, 22, 3].

The other type of context dependence identified is **Temporal Context Dependence**. This refers to the agents' behavior depending on the time of day, or the day of the week, et cetera. That people generally behave differently during the night than during the day (in terms of visited locations, for instance) is obvious, and modeling this time dependence is crucial if one seeks to receive realistic agent behavior over the course of the simulation. For example, individuals who do not work during weekends might be more likely to meet (and potentially spread the disease between) people outside of their usual contact network during these days, which could affect the dynamics of the epidemic spread.

3.5 Deliberation

Are the agents capable to deliberate about actions and their consequences? We define *deliberation* as behavior in pursuit of a goal. This could for instance be implemented as a utility function, a variable to be optimized, agent needs that need to be fulfilled, or the desires or goals in BDI-based models. Models that have agents behave randomly, according to some pre-defined schedule and/or reactively to their environment, are thus not considered to feature agent deliberation. This goal-oriented behavior is common in more advanced models of human behavior [5], and is sometimes even included in the definition of agenthood (see for instance [31]).

Deliberative agents are highly relevant in epidemiological modeling. While agent behavior, in some sense, always is defined by the modelers, doing so by defining the agents' goals or motivations rather than the courses of actions themselves means these courses of actions instead can become results of the model. Such a model could be used to investigate to what extent an agent changes it behavior during the epidemic, or how many agents will comply to a certain intervention. For instance, a model where agents deliberate whether or not to comply with interventions can lead to a deeper understanding of the effectiveness of different interventions than a model which uses fixed compliance rates for interventions. One could even argue that a model with sufficiently advanced cognitive- or psychology-inspired agent behavior could be used to ask *why* agents choose the actions they do, though this sort of analysis puts heavy requirements on the model beyond what we analyze here.

3.6 Norm Compliance

Does the simulation explicitly model legal or social norms which agents do not always comply with? The inclusion of norms in agent-based models has been a prominent research topic [13] and has been argued to be helpful for modeling human behavior [6]. Norm consideration is also one of the five dimensions for comparison used by Balke & Gilbert [5]. If the aim of the simulation is to test the effects of a policy or intervention, whether or not individuals will comply to it will decide its effectiveness and can certainly be an interesting model output in and of itself. Likely this choice will depend both on an individual's needs and preferences, and on the behavior of those around it.

Perhaps the most relevant norm-related question in epidemiological modeling is **Intervention Compliance**. The success of an intervention is largely decided by how many individuals comply with it; a model built on the assumption that all agents follow all mandates without question can only give best-case estimations, and is of less help when asking what interventions actually work. What level of compliance can be expected varies between interventions [26] and between individuals [7].

3.7 Learning

Can agents learn new behavior or information during the simulation? Learning could either mean that agents are able to gather and remember new information (experiences), adapting their behavior to this, or that their decision-making itself can evolve over the course of the simulation. Neural networks or other machine learning methods could, for instance, be used for this purpose, or agents could shift between different behaviors as they discover more information. This aspect is linked to the *Uncertainty Dependence* aspect introduced above (after all, no new information can be learned if all is already known), though it is fully possible to implement an agent with full information of its context which can still learn new behavior over time. Balke & Gilbert [5] use learning as one of their five dimensions for comparison, and it is one of the elements of the ODD and ODD+D protocols [10, 20].

Learning is not considered as crucial for epidemiological modeling as the other aspects discussed above. Still, learning agents could increase the accuracy of human behavior, for instance by having agents learn what public locations to avoid at what times to decrease infection risk, or learn which interventions seem to be effective.

4 Human Behavior In Early COVID-19 Models

To better understand to what extent these aspects are actually considered and implemented by modelers, we analyze early models of COVID-19 interventions. This allows us also to better understand how sophisticated agent behavior is modeled in such models that were explicitly developed to inform policy making. Furthermore, we can assess whether the presented models are sufficiently advanced to support policy decisions and to draw the conclusions they do draw. We focus on early models as these were of highest value for policy makers and might reveal shortcomings in modeling human behavior that prevent modelers from promptly providing adequate support.

To what extent each aspect from Section 3 is modeled can of course vary greatly. In our analysis, we only assess whether or not they have been modeled, thus, not differentiating between, for instance, a model with rich heterogeneity between agents or one with two groups of agents, entirely homogeneous within each group. However, some of the advantages with including an aspect do not hold if its implementation is too simple. Still, we consider the analysis of what aspects of human behavior are ignored altogether to be the first step towards both understanding the focus of current models and identifying areas of improvement. A simple implementation can sometimes be sufficient, but what is not included cannot be studied.

We limit the study to the 126 models previously identified by Lorig et al. [18]. Consequently, only models either published or made available online before October 1$^{\text{th}}$ 2020 were included. This is when the uncertainty reading which interventions to adopt was greatest. Obviously, numerous models were published past this date; however, we are interested in investigating how behavior was modeled in the early models aimed to support policy makers when fast actions were required. From these, we chose the models whose behavioral model had been classified into one of the following categories: *Dynamic or adaptive behavior*, *Fixed behavior*, or *Random (social and spacial network)*. The latter included the more advanced network models, which could include behavior for instance concerning how the agent moves between different networks. Thus, we exclude papers describing models using simple random behavior as well as papers not describing how agent behavior was modeled; in total 96 of the 126 identified models. This selection left us with 30 models, which were chosen as the subject of this study. For the analysis of the models, we extract information from the articles themselves as well as technical details and model descriptions provided in supplementary materials. The source code of models was not reviewed.

Table 1 shows what aspects are include by each of the models according to our analysis. Figures 1 – 6 show to what extent the different aspects were included in models simulating the six most commonly investigated interventions: lockdown, home quarantine, social distancing, testing and tracing, and the closure of schools or workplaces. We have chosen to use the original numbers to refer to the models, see Appendix III of Lorig et al. [18] for the number-to-paper mapping.

Table 1: The papers studied and which of the aspects, as numbered above, they include: 1) attribute dependence; 2a) disease state dependence; 2b) affective dependence; 3) other diseases; 4a) social context dependence; 4b) temporal context dependence; 5) deliberation; 6) intervention compliance; 7) learning. See Appendix III of Lorig et al. [18] for the number-to-paper mapping.

	6	9	10	13	20	23	32	37	41	42	46	47	49	57	59	60	63	64	69	77	80	81	88	90	95	99	103	108	116	125
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2a		x	x	x	x	x	x	x		x	x	x	x	x	x	x	x		x	x		x	x	x	x	x	x	x	x	x
2b							x																							
3					x							x																		
4a						x	x	x		x		x	x	x	x	x		x		x		x			x					x
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Beginning with attribute-dependent behavior, the majority of models (21 out of 30) include this to some extent. The by far most common example of such an attribute was age, with children often being modeled to behave differently than adults. Nearly all models (26 out of 30) modeled agent behavior being dependent of the disease state. Typically, any intervention that asked sick individuals to stay at home includes this aspect. The four models not considering this aspect were network models. Only one model included some form of affective state. In model of Dignum et al. (32), agent behavior is governed by ”needs”, modeled as levels in a number of water tanks. The water level in these tanks can be interpreted as emotions; for instance, a low level of water in the ”safety” tank would indicate emotions of fear, stress, or anxiety in the agent. Other diseases than COVID-19 were only present in two models: Brotherhood et al. (20) and Gopalan and Tyagi (47). Both models included a generic influenza or

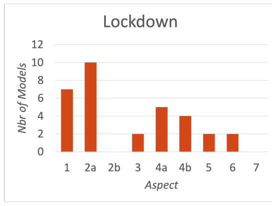

Fig. 1: Aspects in models simulating lockdown. In total 12 models.

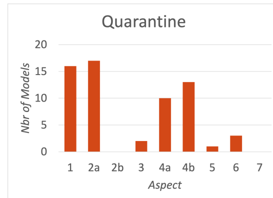

Fig. 2: Aspects in models simulating quarantine. In total 20 models.

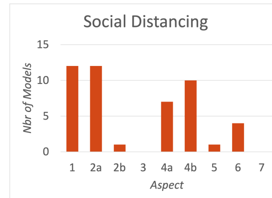

Fig. 3: Aspects in models simulating social distancing. In total 15 models.

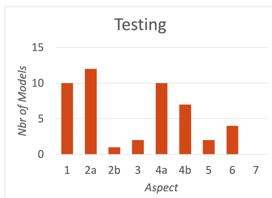

Fig. 4: Aspects in models simulating testing. In total 14 models.

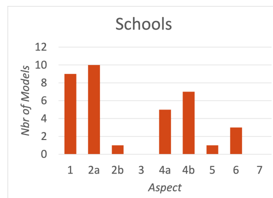

Fig. 5: Aspects in models simulating closure of schools and/or universities. In total 10 models.

Fig. 6: Aspects in models simulating closure of offices or workplaces. In total 12 models.

”common cold” with symptoms similar to COVID-19, spreading independently. Agents are not aware of the specific infection they caught.

Social context dependence is included in around half of the models (14 out of 30). Comparing Figure 4 to the rest of Figures 1 – 6, we see that this aspect is more common in models simulating test-and-tracing strategies. Commonly, social context dependence emerged in the form of household or contact quarantine, meaning that one agent’s health status would affect other agents’ behavior. There exists other examples, however, such as the group activities present in Jalayer et al. (60) or the reduction of agents’ contacts based on their observed infection rate in Karaivanov (64). Slightly more than half (18 out of 30) of the models include behavior dependent on agents’ temporal context. This is most common in models where agents behaved according to some schedule, while network models stand for several of the models without temporal dependent behavior. Three models include agent deliberation. The models varied greatly in their approach to modeling agents: Brotherhood et al. (20) use utility functions to have agents decide how to distribute their time between activities. Dignum et al. (32) use a needs-based model where actions can increase or decrease the level of fulfillment of different needs. Kano et al. (63) take an economical approach. Here, agents have businesses as well as a demand for goods. They can then infect or be infected when they travel to buy goods from other agents. Intervention compliance was modeled in 7 of the 30 articles. The majority of these explicitly defined the compliance rates for interventions as a global parameter. Only Dignum et al. (32) had agents deliberate about whether or not to comply. Finally, none of the models have agents learn new information or behavior.

5 Discussion and Conclusions

In this paper, we have identified seven aspects of agent behavior relevant to simulate realistic behavior of humans. We used these to review human behavior in ABSS models developed in the early stages of the COVID-19 pandemic, in order to understand the current capabilities of ABSS during crises. We found that a majority of the studied models did not include several of the aspects argued to be important for deeper analyses of the effects of interventions. Even in our down-scaled set of papers, most models had agents either follow a schedule defined by the modelers or act stochastically. Only three models included agent deliberation and a single one included an affective state of agents. Moreover, only two models included other diseases than COVID-19. Even looking at more easily implemented aspects, like whether or not agent behavior takes into account the time of day or day of the week, if agents are in any way affected by other agents aside from disease infection, or if there exists any form of heterogeneity in behavior between agents, they are omitted in surprisingly many models. It should be noted that simplicity in models is sometimes argued to be something positive rather than a shortcoming, and trying to force too much detail into a model can be counter-productive [4]. Still, using very simple models puts heavy constraints on what scenarios can be investigated and what conclusions can be drawn.

The discovered simplicity should not be taken as representative of the best that the ABSS community in general can do in terms of modeling human behavior; rather, it indicates what we can accomplish given a very restricted amount of time and data. Several more advanced models of human behavior in social simulation has been developed than what has been seen here [15]. As mentioned, modeling in response to emergencies is highly difficult. Many of the simplifications made in the models can be assumed to have been made out of necessity, due to the lack of data and urgency of results. This is not a reason to accept that models of crises are bound to be flawed and in some cases untrustworthy, however. Rather, it poses the question of what can be done to prepare for the next emergency, epidemiological or otherwise.

One such challenge concerns the tools available to implement human behavior. A large number of tools and software exists for building agent-based models [1], however, the results of this study seem to indicate either that their support to build realistic human behavior (such as ready-to-use deliberation models) is too limited or that this functionality is ignored or unknown to modelers. A second challenge concerns reusing existing models. While there existed instances of models built for previous epidemics being repurposed for COVID-19, a large number of the models were built from scratch. This could result in researchers reinventing the wheel instead of building on more advanced models. Of major importance then is that models are built and communicated with reusability in mind. A third challenge concerns the availability and usage of data. We should not have to start from zero regarding behavioral responses to each new emergency. Presumably, the behavior observed during the COVID-19 pandemic and other crises hold answers to how individuals behave in a broader context than in that of each specific crisis. Such answers could relate to calibration of deliberation functions and affective responses, as well as having compliance rates be an output of such a deliberation function rather than input to models. This requires not only thorough analysis of previous crises, but also that data on these are available to modelers and, crucially, that it is collected in the first place.

Future studies could include seeking to further validate the aspects presented in this article through applying them to more cases in which human behavior is being modeled. It would also be of value to analyze more recent models of the COVID-19 pandemic, in order to understand if and how the models of human behavior have improved with time and increased data availability. On a larger scale, tackling the three challenges outlined above would require substantial effort, but if we do so, ABSS modelers would be much better equipped for potential future crises. By giving ourselves the best possible conditions to tackle future crises, we can rest a little less worried of what the future might hold.

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