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Evaluation of Contact-Tracing Policies against the Spread of SARS-CoV-2 in Austria: An Agent-Based Simulation

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Background. Many countries have already gone through several infection waves and mostly managed to successfully stop the exponential spread of SARS-CoV-2 through bundles of restrictive measures. Still, the danger of further waves of infections is omnipresent, and it is apparent that every containment policy must be carefully evaluated and possibly replaced by a different, less restrictive policy before it can be lifted. Tracing of contacts and consequential breaking of infection chains is a promising strategy to help contain the disease, although its precise impact on the epidemic is unknown. **Objective.** In this work, we aim to quantify the impact of tracing on the containment of the disease and investigate the dynamic effects involved. **Design.** We developed an agent-based model that validly depicts the spread of the disease and allows for exploratory analysis of containment policies. We applied this model to quantify the impact of different approaches of contact tracing in Austria to derive general conclusions on contract tracing. **Results.** The study displays that strict tracing complements other intervention strategies. For the containment of the disease, the number of secondary infections must be reduced by about 75%. Implementing the proposed tracing strategy supplements measures worth about 5%. Evaluation of the number of preventively quarantined persons shows that household quarantine is the most effective in terms of avoided cases per quarantined person. **Limitations.** The results are limited by the validity of the modeling assumptions, model parameter estimates, and the quality of the parametrization data. **Conclusions.** The study shows that tracing is indeed an efficient measure to keep case numbers low but comes at a high price if the disease is not well contained. Therefore, contact tracing must be executed strictly, and adherence within the population must be held up to prevent uncontrolled outbreaks of the disease.

Keywords
agent-based modeling, covid-19, epidemics model, modeling and simulation, sars-cov-2

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Since the SARS-CoV-2 spread worldwide in March 2020, countries managed to stop the exponential increase of case numbers several times (for example, see situation report 88 by the World Health Organization[1]). Besides a few countries in Asia, such as China and South Korea, most of the countries in Europe have so far succeeded in containing the disease because of the swift and rigorous policy making of their governments. With these measures, they averted a potential overload of their health care systems, as happened in the Lombardy region in Italy in March[2,3] or in Wuhan, China, in January.[4] Of these European countries, including Germany, France, and Norway, Austria stands out due to its especially fast policy making in March, which allowed the country to rapidly overcome the first wave of disease.

Most of the introduced policies, such as closing schools, shops, and restaurants, proved to be effective in stopping the initial growth of the pandemic and led to a

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decrease in the number of new infections per day. However, due to social and economic reasons, lockdown policies cannot be upheld long enough to eradicate the disease completely.[5] After a certain time, most of these measures must be lifted again, while other actions must be enforced to prevent a new upswing of the disease.

Testing and subsequent isolation of detected cases are the cornerstone of the disease containment program of COVID-19. Hereby, tests are used to evaluate the disease status of a suspected infected person, who needs to isolate in case the test is positive. The success of this strategy is directly coupled with the sensitivity of the test and the time it takes for a person to become infectious and symptomatic, initiate the test, take the test, and finally receive the test result—with the less time elapsed during this process, the better. Because this period usually spans a couple of days, secondary infections can be reduced but not entirely prevented this way.

The concept of contact tracing directly follows this idea. The essence of this strategy is to find and isolate those who might have already been infected by any newly confirmed case. Now, time is in favor of the regime, since the tracer is looking for secondary transmissions and the disease is much less advanced in the affected persons. Consequently, it is now possible to find and isolate infected persons much earlier in their disease pathway, potentially even before they become infectious.

Although stigmatized as a violation of personal freedom, tracing is not always related to personal data–tracking devices such as mobile apps.[6] Successful tracing of contacts starts with the isolation of household members or by temporarily closing workplaces of persons confirmed to be infected with SARS-CoV-2. Many potentially infectious contacts can be traced by a simple interview with the patient as well.

Yet, besides many successfully detected and isolated newly infected persons, many entirely unharmed, healthy contact partners would also be put into quarantine this way. This results in unintended adverse health effects and socioeconomic losses and can therefore be interpreted as a drawback of the strategy.

Finding evidence that proves or quantifies the success of different tracing strategies is still difficult, for 2 reasons: on one hand, because of the novelty of the situation, and on the other hand, because simulation models are currently the only possibility for estimating the future impact of strategic changes. In Austria, simulation results are systematically used by the ministry of health and public health authorities to guide health policy decision making and planning. The authors of this study are part of this process.[7]

In this article, we apply an agent-based model (ABM) that is also subject of this study and fully documented in the Methods section and the Appendix. In contrast to typical aggregated compartment models, such as the classic SIR model by Kermack and McKendrick,[8] ABMs do not treat the population as one continuously changing variable but as the aggregate of individually modeled entities, so-called agents.[9,10] Consequently, not only the transmission of the disease but also policies such as contact tracing can be modeled via agent-agent interaction laws. This approach poses a low level of abstraction as compared with reality.

The key objective of this work is the qualitative and quantitative analysis of tracing as a containment policy for the COVID-19 pandemic. We identify which tracing strategy is the most successful, comes with the least socioeconomic costs, under which circumstances it works best, and whether the disease can be contained by this measure alone or if additional policies are needed.

Methods

For the development and analysis of our model, we followed the international guidelines of the ISPOR-SMDM Joint Modeling Good Research Practices Task Force[11,12] in the selection and justification of the model type as well as the description of methods and the reporting of our results.

We applied an ABM strategy in which each inhabitant is statistically represented by a model agent with certain demographic and disease-related features. Disease transmission occurs via contacts between agents, which occur inside of locations where agents interact with each

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other. The model is capable of introducing certain policies, in particular different tracing strategies, that change the behavior of the agents and/or the transmission behavior of the disease.

Model Type

The chosen ABM type is a complex approach for the simulation of epidemics, and there is a large variety of simpler simulation methods, such as the classic differential equation–based SIR cohort model by Kermack and McKendrick.[8] These strategies would be preferred if the sole purpose of the modeling process was the simulation of the disease. Yet, modeling of contact-tracing policies requires modeling of person-to-person contacts, which excludes population-based model types (see Pitman et al.[12]). Consequently, a stochastic agent–based approach is necessary.

The model is comparable with similar models developed for Australia[13] and the United Kingdom[14] but stands out by several features described in detail below. Briefly,

1. our model is based on a precise spatial and demographic image of the Austrian population in which each Austrian citizen is represented as an agent,
2. it uses a contact network based on different locations, such as households, workplaces, and schools, and
3. it allows for tracing of agent–agent contacts and, consequently, for analysis of related tracing policies.

Decision-Analytic Framework of the Policy Question

The target population of our study includes the entire population of Austria in the year 2020. The analytic time horizon of our analysis is February 21 to November 15, 2020, whereas the interval from February 21 to April 9 is used for calibration of the model, and the time span between April 9 and December 15 is the actual simulation interval.

For the actual evaluation of tracing policies, we investigate and compare 6 different strategies: 1 strategy without tracing (no tracing), 3 strategies with location tracing (household tracing, workplace tracing, combined household and workplace tracing), and 2 different strategies of direct contact tracing. Since containment strategies for diseases are always a bundle of measures, we will evaluate each of the tracing strategies in combination with additional contact reduction. In this process, 2 different reduction values will be applied: one that will cause the case numbers to remain constant and one that will cause the numbers to decrease. For details, refer to the "Strategies and Scenarios" section of this article.

We use our simulation to observe the timeline of the COVID-19 cases in different stages of the disease and treatment. We distinguish presymptomatic (infected within the incubation period), preconfirmed (sick persons waiting for a test/test result), undetected (infected persons who are and will never get tested because they have no/mild symptoms), and confirmed (cases confirmed by a positive test), as well as isolated (cases who must stay at home due to a positive test) and preventive quarantine (persons put under preventive quarantine by a tracing policy). We track these numbers in 3 different forms: active (total number of persons in this state for a given point in time), cumulative (total number of persons who have ever been in this state since the start of the simulation), and new (number of persons who entered this state within the past day). To compare tracing strategies, we define the cost measure quarantined per infection prevented ($QpIp$), which is calculated as

$$QpIp(t) = \frac{Q_t}{I_0 - I_t}, \tag{1}$$

where I_0 stands for the cumulative number (measured from the day of the policy introduction on May 15) of new infected agents in the no-tracing scenario, I_t describes the analogous number in the observed tracing strategy, and Q_t stands for the cumulative number of preventively quarantined agents in the observed tracing scenario. This value can be interpreted as a cost function for the tracing strategy t.

The model uses a comparably high number of parameters that are identified using various data sources. Some values are determined using data from the published literature, some are taken directly from census or routine data, some values are based on expert estimates, and some values require calibration routines.

Population parameters including fertility, mortality, and migration are identified via official publicly available census data from the Austrian national statistics office, "Statistics Austria." Parameters related to the contact behavior are primarily based on the POLYMOD contact survey,[15] but open-source data from Statistics Austria and the official data repository of the city of Vienna about household structure, employment rate, schools, and workplaces have also been used.[16–18]

COVID-19–related parameter values are based on recently published literature, expert opinions, the official disease reporting system of Austria, and calibration processes. Time spans, such as incubation time, disease

duration, and so forth, are parametrized using information from refs. 19 and 20 and opinions from local virology experts. Hospitalization ratios and age distributions are gathered from statistical postprocessing of data from the official COVID-19 reporting system of Austria, the Epidemiologisches Meldesystem (EMS[21]). The probability of an asymptomatic (undetected) disease progression is based on early antibody tests from Iceland.[22] Finally, the infection probability and the impact of the already implemented lockdown measures in Austria were calibrated using the officially reported Austrian COVID-19 cases by EMS as a reference.

For more details on all parameters and all parameter values used, the reader is referred to the Appendix, Section A1.3.3.

Model Specification

According to the Modeling Good Research Practices guidelines,[11] we state a short, but easily understandable, model description here. For a detailed and reproducible one, see the Appendix, Section A1.

The developed ABM is stochastic, population dynamic, and depicts every inhabitant of Austria as one model agent. It uses sampling methods to generate an initial agent population with statistically representative demographic properties and makes use of a partially event-based, partially time step (1 day)–based update strategy to enhance in time.

Model input. The model's input consists of an event timeline of strategies that change the dynamics of the model at certain dates, mostly policies introduced by the government. In the simulation, each element of the timeline is translated to 1 model-event that changes certain parameters or model mechanisms at the specified event time. In addition, this feature of the model enables a comparison of different strategies with each other, also regarding the introduction time of the strategy.

Model initialization. Starting the simulation executes a population-sampling routine, which has been implemented in the course of a prior research project (see DEXHELPP[23]). This sampling routine, a part of the Generic Population Concept (GEPOC[24]), ensures that the demography of Austria is well depicted by the agent population, meaning statistically correct age, sex, and residence of each agent.

Moreover, the start date of the COVID-19 simulation model must lie between March 2020 and the current day, and the simulation may be run arbitrarily long. To start the simulation at the defined point in time, say t_0, the model applies an initialization simulation run from February 2020 until t_0 to 1) calibrate the model parameters to the time series of the confirmed COVID-19 cases in Austria until t_0 and 2) to generate a valid initial agent population for the actual simulation. This process guarantees that the correct number of susceptible, infectious, hospitalized, and so forth model agents are present when the actual simulation is started.

The dynamics of the model are given by the interplay of 4 different submodels: a population, contact, disease, and policy model.

Population model. In each time step, agents are affected by demographic changes including age and time-specific mortality and fertility rates. Based on that, each agent has a certain time- and age-dependent probability to die or produce offspring any time during the simulation. Migration behavior is neglected in the model because of restricted immigration rules in Austria in reality.

Contact model. Moreover, the model makes use of a location-specific contact model to establish interactions between agents. Agents meet daily at workplaces, schools, households, and in leisure time and can transmit the virus with a certain transmission probability, if they are infectious.

Disease model. After being infected, agents go through a detailed disease and/or patient pathway that depicts the different states of the disease and the treatment of the patient. This pathway, shown in Figure 1, is modeled via specifically distributed transition times and is not Markovian. It contains branches with respect to disease severity (mild, severe, critical, etc.) as well as treatment (hospitalization or home isolation, normal bed or intensive care unit, etc.) and always ends in the recovery or death of the agent. The disease and treatment states influence the contact behavior of the agent and, consequently, how it can transmit the virus.

Policy model. Clearly, not only the disease and treatment state but also the currently active policies influence the contact behavior of the agents. Policies may lead to closure of certain locations, which make them unavailable for contacts but may also cause a reduction of contacts or a reduction of the infectivity of contacts because of increased hygiene. The focuses of the present study are tracing policies that cause additional home quarantine for contacts of newly infected agents, removing them

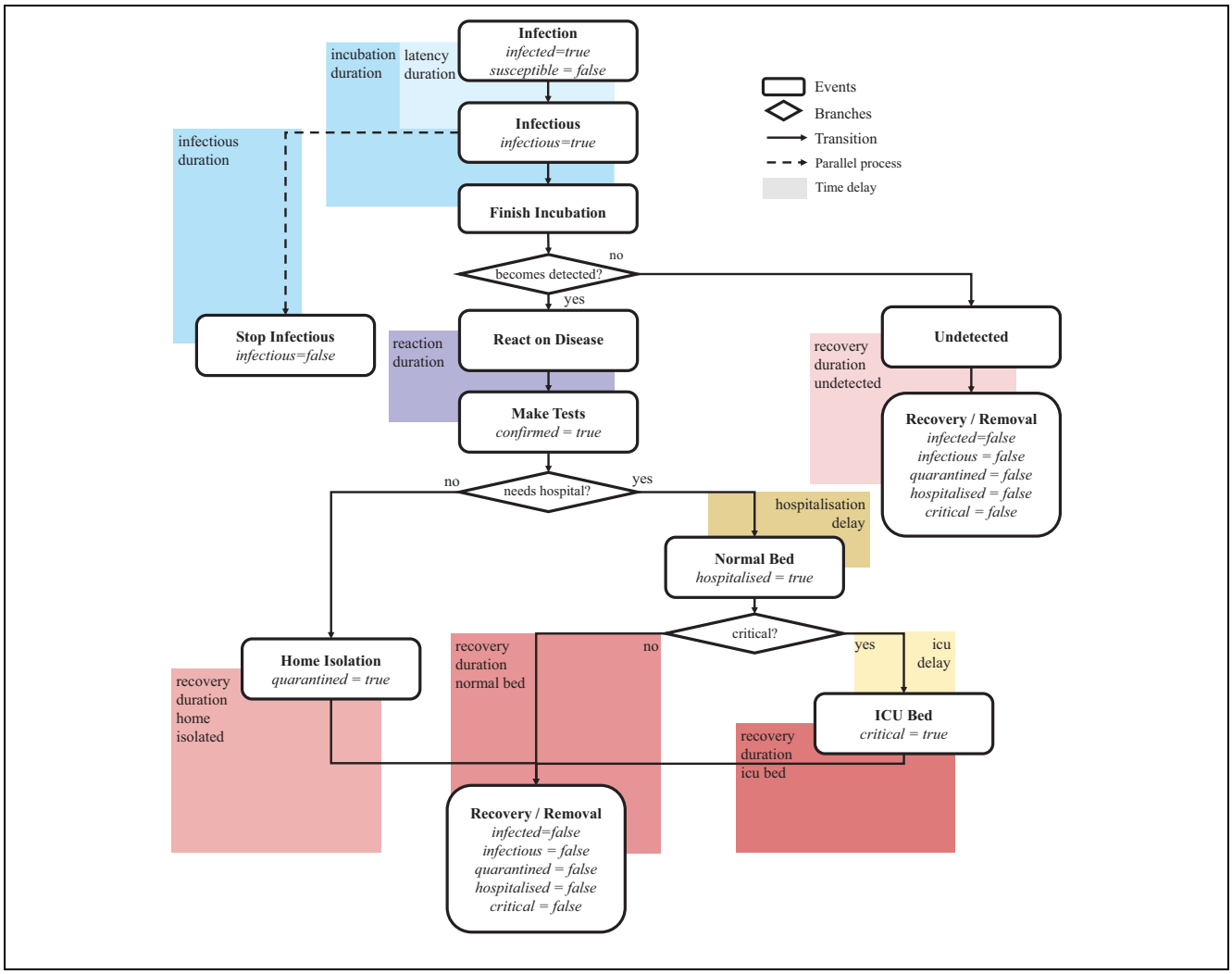

Figure 1 State chart of the patient pathway of a person-agent in the agent-based simulation model. Only those state variables that are changed by the corresponding event are labeled; all others remain at the current value. The initial state of all infection-specific state variables is false, except from susceptible, which is initially true.

from the contact network and reducing the likelihood that the agent transmits the disease.

Model output. The outcomes of the model are time series with a daily time basis. They consist of aggregated numbers describing the current nation- and/or regionwide spread of the disease as well as numbers depicting the contact behavior of agents. These include, for example, the cumulative number of confirmed cases, the number of currently active asymptomatic cases, the total number of daily newly infected 10- to 30-y-old females, the total number of daily contacts for school children, or the average number of secondary infections per agent ($=R_{eff}$). The outcomes observed for this study in particular are explained in the "Decision-Analytic Framework of the Policy Question" section.

Model Implementation

The simulation of ABMs such as the specified agent-based COVID-19 model is a huge challenge with respect to computational performance. Because the model cannot be scaled down, almost 9 million interacting agents need to be included into the model to simulate the spread of the disease in the entire population of Austria.

These high demands exclude most of the available libraries and software for ABM, including AnyLogic, NetLogo, MESA, JADE, or Repast Simphony.[25–29] Most of these simulators cannot be used, as their generic features for creating live visual output generates too many overheads.

Consequently, we decided to use our own agent-based simulation environment ABT (Agent-Based Template[30]), developed in 2019 by dwh GmbH in cooperation with TU Wien. The environment is implemented in JAVA and specifically designed for supporting a reproducible simulation of large-scale agent-based systems. More technical details are found in the Appendix, Section A3.

Strategies and Scenarios

To achieve the goal of comparing different tracing strategies, we describe the tracing strategies and compliance scenarios mentioned in the "Decision-Analytic Framework of the Policy Question" section and define them in the upcoming 4 sections. The initialization phase of the model is defined in the "Definition of the Initialization Phase" section, the reference strategy without tracing and the 3 strategies dealing with location tracing are defined in the "Definition of No-Tracing and Location-Tracing Strategies" section, and 2 strategies with different types of individual tracing are specified in the "Definition of Individual Tracing Strategies" section. The concept for additional contact reduction policies is presented in the "Definition of Stagnation Levels and Contact Reduction Strategies" section.

At some points, the specification of the strategies and scenarios are not fully reproducible to support readability. For tables containing the precise, reproducible model parametrization, we refer to the Appendix, Section A4.

Definition of the Initialization Phase

We chose April 9, 2020, 08:00 AM as the initial time of our actual simulation; we will henceforth denote this time as t_0. To start the simulation at this date, it is necessary to run an initialization phase that validly depicts the entire progression of the disease until this date and to save the final state of this phase as an input to the actual simulation. Interestingly, this initialization phase also reveals certain features about the disease that cannot be measured in the real system, for example, the time series of the asymptomatic cases. Consequently, we decided to include this initialization phase to this study as an initial scenario.

By April 9, the countrywide lockdown in Austria had already managed to reduce R_{eff}, the effective transmission rate of the disease, below 1, causing the number of newly infected people per day to decrease. About 12,900 positive virus tests had been reported until this date.[i] To guarantee that the final state of the initialization phase matches this number, a calibration process was performed adjusting both infectivity and impact of lockdown policies. This process is, in more detail, described in the Appendix, Section A1.3.4. The country implemented nationwide closure of schools and workplaces on March 16, yet our calibration process revealed that this lockdown should rather be modeled as a process with several steps, which are briefly listed in the Appendix, Table A7. It is apparent that the modeled policy events and, in particular, their parametrization cannot be taken into account separately; some of them might have a larger and some a smaller impact in reality than in the model. However, the summary of all policies allowed us to calibrate the current curve of the disease by feasible and causally founded assumptions.

Definition of No-Tracing and Location-Tracing Strategies

On May 1, all containment measures have been lifted, subsequently raising R_{eff} to greater than 1. In the simulation, all tracing policies have been implemented on May 15, a time at which the new upswing of the epidemic could already be observed by an increasing number of new infections, independent of the compliance level.

To create a reference for the evaluation of tracing strategies, we specified a no-tracing strategy in which no tracing is present whatsoever. As soon as infected agents become confirmed cases, they isolate themselves, but there are no consequences for contact partners whatsoever.

As the first public health measure to evaluate, we established so-called location tracing policies. We define this policy as the reaction of a person's direct surrounding in response to a positive SARS-CoV-2 test result. While isolation of the affected person is done as usual, now all persons in the direct surrounding of the infected person will become isolated as well, independent of their current disease state. In this process, the surrounding is defined as the group of persons who commonly visit the same locations as the infected person. By this measure, we expect to find and isolate a high percentage of infected persons before they even become visible to the system.

In the model, we studied the effects of location tracing regarding 2 location types: household and workplace. The policy "household tracing" means that as soon as an agent enters the confirmed status, all other members of

the agent's household are isolated as well. In "workplace tracing," the workplace of a confirmed COVID-19 patient is temporarily closed, and all coworkers are put into preventive quarantine.

In isolation, agents only have contact with other members of their household. They do not attend school or work and do not have leisure-time contacts. After a fixed number of days (we chose 14 d for our strategies), agents are released from isolation and can resume their normal behavior, if they turn out to be unaffected by the virus. Clearly, the availability of a precise test could reduce the required quarantine length, yet this feature is not included in the model, thus providing conservative estimates.

We evaluated the impact of the location tracing for households and for workplaces separately as well as in combination, henceforth denoted as the "combined tracing" strategy.

Definition of Individual Tracing Strategies

Extending the ideas of location tracing, we studied the effects of individual tracing of contacts. For this tracing policy, we assume that a certain amount of people record their contacts outside of their household, for instance, by using a tracing app on their smartphone or on a similar device. In this process, a contact is recorded if both involved persons use the tracing device. We assume that the tracing is completely accurate. In this way, all contacts between persons using the tracing device are recorded, and most importantly, there is no infection between 2 tracing people that goes undetected. These contacts are saved for a specific recording period. If a person using the tracing device becomes a confirmed case of COVID-19, the recorded contacts are informed and placed under preventive quarantine. The implications of the preventive quarantine are the same as in the "Definition of No-Tracing and Location-Tracing Strategies" section.

The effectiveness of this policy has been evaluated on top of the location-tracing policies for households and workplace contacts, that is, the combined tracing strategy. We considered rates of 50% and 75% of people using the tracing device and a recording period of 7 d. The length of the preventive quarantine is fixed at 14 d.

Definition of Stagnation Levels and Contact Reduction Strategies

Contact tracing is a part of the portfolio of public health interventions that do not interfere with daily activities of the whole population. Therefore, we want to quantify how various contact-tracing policies might be able to reduce the need for additional public health interventions. When evaluating the impact of a containment policy via modeling and simulation, one difficult problem, in particular, arises.

When evaluating the impact of a containment policy via modeling and simulation, the policy cannot be evaluated without thinking about additional measures that are active at the same time. Consequently, scenarios with assumptions for additional policies need to be made to evaluate the impact of the policy in the context of other measures. This might also cause problems, because not every policy is suitable in combination with any other policy or for any state of the pandemic. In particular, the analyzed contact-tracing policies are not applicable if the case numbers exceed a certain boundary because of limited human resources.

To overcome this problem, we define the stagnation level of a contact-tracing policy as the reduction in transmission needed from other public health policies to keep disease levels at a steady state. As the tracing policy alone does not sufficiently suppress further infections to reduce R_{eff} below 1, we introduce the stagnation level. This is the percentage of additional reduction of disease infectiveness in leisure time, workplaces, and schools necessary to keep the disease numbers on a constant level, which means they neither decrease nor increase. The higher the stagnation level, the more additional policies need to be introduced for disease containment and the less effective is the tracing strategy.

Technically, finding these stagnation levels is related to a calibration process. In this process, the calibration value is the parameter of an infectivity reduction event scheduled for leisure time, workplace, and schools, which is scheduled for May 15 (the same date as the introduction of the tracing policy). The value is calibrated between 100% (contacts are not infectious anymore) and 0% (contacts are fully infectious, that is, as infectious as calibrated in the initialization phase scenario). A standard bisection method is used with a Monte Carlo simulation (12 runs each) in the loop. Because stagnation of the case numbers is the goal of the calibration process, the target value of the calibration routine is defined as the slope of the regression line fitted through the simulated time series of the new confirmed cases per day between June 1 and July 1.

Figure 2 shows an image of the calibration process for the stagnation levels of the no-tracing policy. The case numbers for the time between April 9 and May 1 are dropping because of the upheld lockdown measures. On May 15, the infectivity reduction event damps this

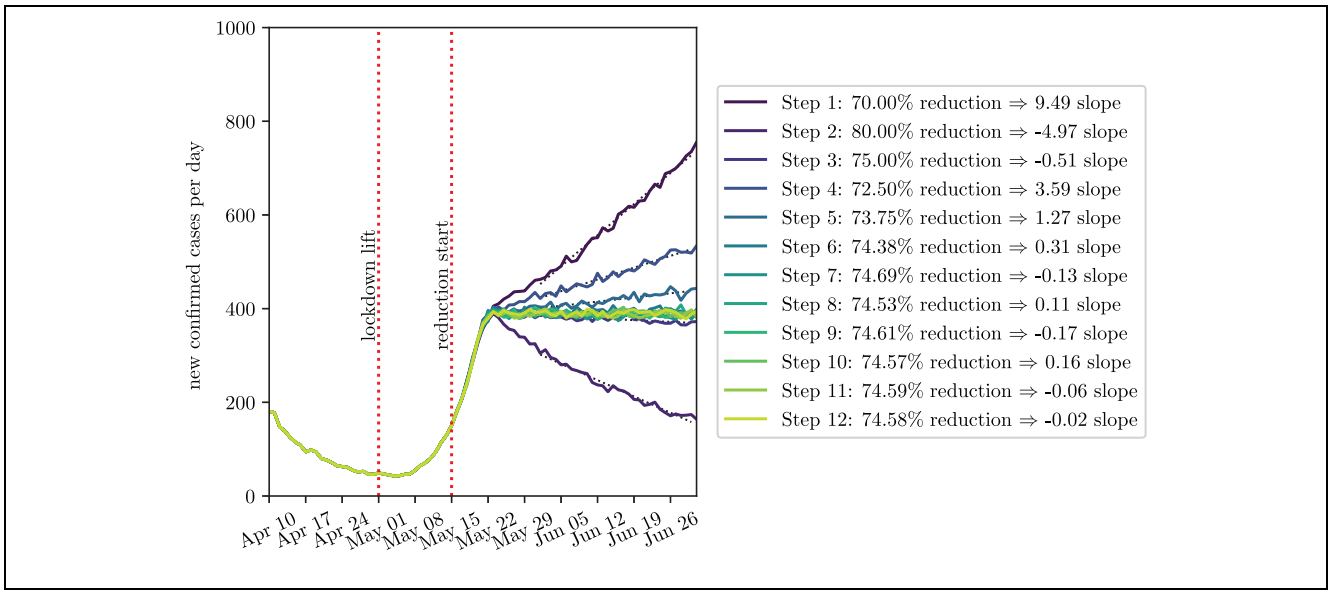

Figure 2 Calibration process of the stagnation level for the no-tracing strategy. The color map indicates the sequence of bisection steps the calibration routine has performed with respect to the varied parameter: the infectivity reduction on May 15. The black dotted curves show the regression lines used for evaluating the calibration target: the slope of the regression line.

upswing and is calibrated to cause stagnating numbers. The calibration routine terminates for 74.58% infectivity reduction in leisure time, workplaces, and schools, which causes the case numbers to stagnate at about 390 new confirmed cases per day. According to the specified ratio of undetected cases, this corresponds to about 2000 new infected cases per day, as depicted in Figure 3.

Note that the bisection algorithm does not always generate a fully monotonically converging result because of the stochasticity of the simulation. Even though Monte Carlo simulation is used to filter the effects of the stochastic model, a small level of perturbation remains. Consequently, the results of the algorithm are precise up to the second decimal.

In the following, we use the concept of stagnation levels to compare the tracing policies. First, we determine the stagnation levels of all 6 tracing policies and compare these with each other. This way, we will determine how much contact reduction can be compensated by which tracing policy. In a second step, we will simulate each of the six tracing policies together with the stagnation level of the no-tracing strategy (depicted above). This way, we will determine how different tracing strategies affect the decline of the case numbers.

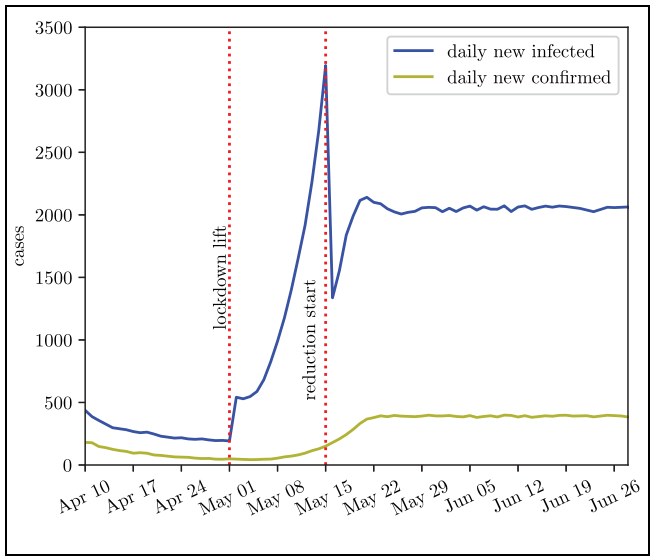

Figure 3 Curves for the daily new confirmed and the new infected cases for the no-tracing strategy when calibrated to the stagnation level (74.58%). The lift of the lockdown as well as the introduced infectivity reduction instantaneously reduces the level of new infections, while the change for the new confirmed cases happens more smoothly and is time delayed.

Table 1 Calibrated Stagnation Levels for All 6 Contact-Tracing Strategies[a]

Tracing Strategy	Stagnation Level (%)	Stagnation Level Improvement Compared with No Tracing (%)
No tracing	74.58	—
Household tracing	72.96	1.62
Workplace tracing	73.53	1.05
Combined tracing	71.47	3.11
50% individual tracing	70.46	4.12
75% individual tracing	69.40	5.18

[a]Higher stagnation levels indicate that more contact/infectivity reduction policies need to be added to the tracing strategy to contain the disease.

Results

Initialization Phase

On average, by March 16, the modeled total contacts per day were reduced by about 78%, with additionally reduced infectivity of contacts at workplace and in leisure time by 50%. That is, the March lockdown in Austria resulted in a total infectivity reduction of the disease by about 89% $(1-(1-0.78)(1-0.5))$.

For calibration purposes, a bisection algorithm was applied to iteratively improve the value of one parameter value after the other. This strategy is possible as the impact of the calibrated parameters can be measured at different points in time: the base infection probability can be calibrated in the period before the introduction of measures, the impact of the first policy can be calibrated in the period between the first and the second, and so forth. Hence, the multidimensional calibration problem can be decoupled into several scalar ones. More on this strategy is found in the Appendix, Section A1.3.4. The calibrated parameters as well as a plot comparing the real reported cases and the confirmed cases from the calibrated model are found in Appendix A4.

Stagnating Case Numbers

In the first comparison of tracing policies, we used the concept of stagnation levels introduced in the "Definition of Stagnation Levels and Contact Reduction Strategies" section. We used the presented calibration routine for all 6 strategies and determined the corresponding stagnation levels. They are summarized Table 1.

Moreover, we compared the simulation results for all 6 tracing strategies together with the correspondent infectivity reduction on stagnation level. While the curves of the new confirmed cases all show the same picture as the one seen in Figure 2, the numbers of new preventively quarantined agents differ because of different strictness of the tracing policies. This is displayed in Figure 4. The scenarios involving workplace tracing show an unsteady increase in quarantined agents directly after start of the policy. This results from instantaneously putting all workplaces containing confirmed infected agents under quarantine, the moment the policy is introduced. Analogous to the new confirmed cases, the new quarantined agents also converge to equilibrium values, which correspond to the strictness of the tracing strategy.

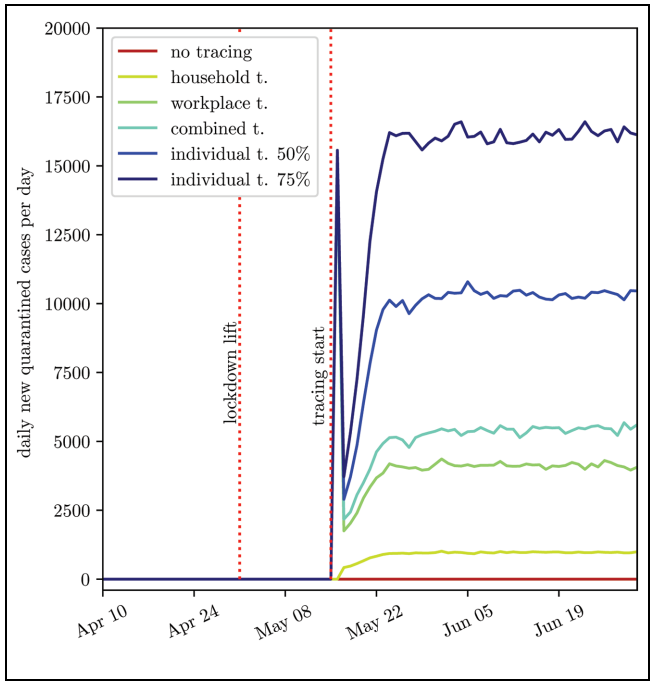

Figure 4 Simulation results for the new preventively quarantined agents, that is, agents put under preventive quarantine as a traced contact. All 6 tracing strategies are evaluated in combination with the corresponding infectivity reduction for reaching the stagnation level.

Decreasing Case Numbers

In a second step, we evaluate the performance of the tracing strategies for a contained scenario. To do this, we

Table 2 Summary of Simulation Results for All 6 Tracing Strategies Simulated Together with 74.58% Infectivity Reduction

Tracing Strategy	Cumulative Infected Agents (May 15–Nov 15)	Difference to No-Tracing Strategy	Cumulative Preventively Quarantined Agents (May 15–Nov 15)	Quarantined per Infection Prevented (*QpIp*)
No tracing	371,709	—	—	—
Household tracing	220,046	151,663	104,182	0.69
Workplace tracing	244,092	127,616	530,078	4.15
Combined tracing	165,167	206,542	458,006	2.22
50% individual tracing	141,822	229,887	735,792	3.2
75% individual tracing	119,826	251,883	970,461	3.85

fix the infectivity reduction on the stagnation level of the no-tracing strategy, that is, 74.58%, and run the simulation for each of the 6 tracing strategies. The curves for the new confirmed cases are displayed in Figure 5. Clearly, result curves start to diverge from May 15 since policies are introduced at this date. Thereafter, more strict tracing policies cause a faster decline of the case numbers. Results including information about the preventive quarantined persons are summarized in Table 2, including the cost measure *QpIp* defined in Equation 1.

Figures 6 and 7 provide an image of the cost measure showing the cumulative quarantined and the prevented infections in relation to each other. Specifically, Figure 7 clearly displays that the ratio between these values is time dependent. The corresponding values are found in Table 3.

Discussion

We implemented an agent-based simulation model that not only can be calibrated to match the previous course of the COVID-19 epidemic wave in Austria but is also capable of making comparisons between various non-pharmaceutical intervention strategies. In this study, we applied this model to compare tracing policies in different characteristics and evaluated them with respect to socioeconomic costs in the form of preventively quarantined people.

Evaluation of Tracing Policies

The model results indicate that tracing, in any form, is a suitable policy to reduce secondary infections and is an efficient supplement to lockdown policies for containing the spread of the disease. The results depicted in Table 1 indicate that well performed contact tracing would supplement about 5% contact or infectivity reduction. In contrast to the required 75% reduction for full containment of the disease, this would correspond to only 1 small part of the full containment strategy. Yet, since tracing is one of the few strategies that does not imply restrictions for daily activities, such as closure of schools or limitation of movement, it must not be underrated. Note that all of the presented strategies are applied on top of a classical quarantine strategy in which any positively tested person is isolated. This is, essentially, the basis of any containment strategy and therefore a persistent element of the base model.

Anyway, isolating persons because of a preventive quarantine measure is always related to unintended economic and sociopsychological adverse effects, which is particularly critical if the isolation turns out to be unnecessary. Consequently, any tracing measure should focus on keeping the total number of isolated persons as small as possible to reduce socioeconomic damage. The defined cost value *QpIp* is used to quantify the efforts of a specific tracing strategy. It relates to the direct benefit of the policy and directly correlates with the accuracy of the measure, that is, the probability that a preventively isolated person is not only potentially but actually infected. Thus, the model suggests that isolation of household members is the most accurate measure and leads to the highest number of infections averted in relation to quarantined persons. Temporary closing of only workplaces due to positive cases is clearly the least accurate and therefore the costliest of the modeled policies. Combining the 2 policies and adding leisure-time contact reduction also results in a more costly strategy, yet a greater reduction in infectivity can be reached because more secondary infections are found and isolated. The model results show that tracing might require up to 4 times as many quarantined as infected persons for the least accurate tracing method (individual tracing with 75%) and about 0.7 times as many for the most accurate tracing method (preventive household quarantine). Considering that polymerase chain reaction (PCR) tests used to detect the index case are not 100% specific in reality, false-positive cases would be found and traced contacts would also be

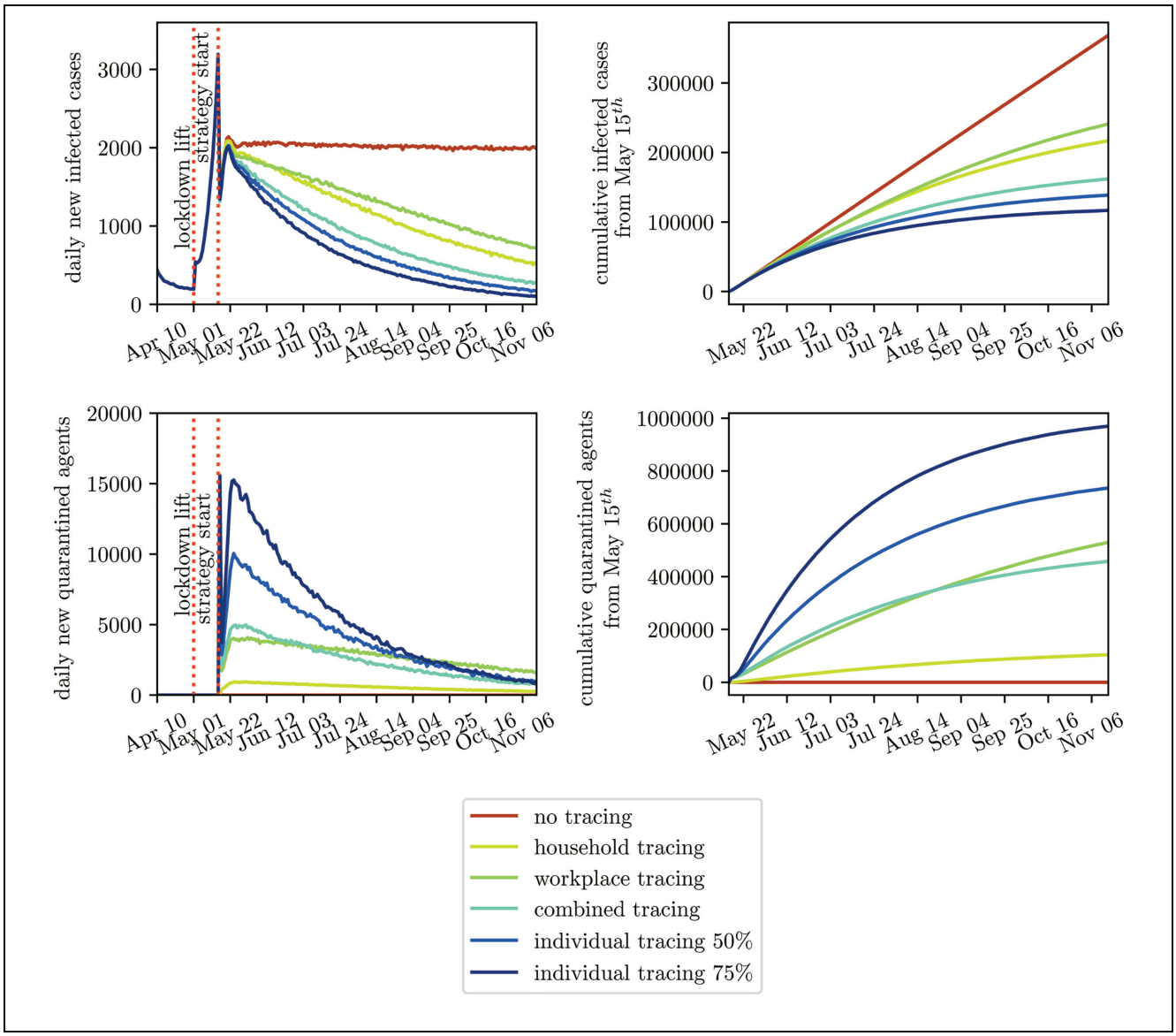

Figure 5 Simulation results for all 6 tracing strategies simulated together with 74.58% infectivity reduction are displayed. The left plots show the new confirmed and new preventive quarantined cases. The right plots display the correspondent cumulative curves, calculated from May 15.

put falsely under quarantine. Since our model does not consider tests of healthy people, false-positives are not depicted. Hence, the ratio between quarantined and infected and also the *QpIp* values would be slightly higher in the real system than that displayed above, dependent on the specificity of the test and the prevalence in the tested cohort.

In summary, the model results imply that a tracing strategy can be evaluated in terms of effectiveness, that is, how much contact reduction can be supplemented by the strategy, and in terms of accuracy, that is, how many persons need to be quarantined in relation to the averted infections. Furthermore, the results imply that there is a tradeoff between these values, at least for the tracing strategies observed in this work.

Moreover, Figure 7 and Table 3 suggest that an inaccurate tracing method might also pay off in the long run if it is an effective one. This is due to highly interesting dynamics caused by the interplay of the 2 feedback loops depicted in Figure 8. If the feedback loop of the

Table 3 Change of the Quarantined per Infection Prevented (*QpIp*) Value over Time for the Different Strategies

Tracing Strategy	$\frac{Q_t}{I_0-I_t} = QpIp$ for May 15th – Jul 15th	$\frac{Q_t}{I_0-I_t} = QpIp$ for Jul 15th – Sep 15th	$\frac{Q_t}{I_0-I_t} = QpIp$ for Sep 15th – Nov 15th
Household tracing	$\frac{47764}{124756-107294} = 2.74$	$\frac{35495}{125243-71169} = 0.66$	$\frac{20923}{121710-41583} = 0.26$
Workplace tracing	$\frac{228051}{124756-107960} = 13.58$	$\frac{179316}{125243-81668} = 4.12$	$\frac{122712}{121710-54465} = 1.82$
Combined tracing	$\frac{250154}{124756-92843} = 7.84$	$\frac{139428}{125243-48769} = 1.82$	$\frac{68424}{121710-23555} = 0.70$
50% individual tracing	$\frac{434501}{124756-87049} = 11.52$	$\frac{210606}{125243-38535} = 2.43$	$\frac{90684}{121710-16237} = 0.86$
75% individual tracing	$\frac{622313}{124756-80069} = 13.93$	$\frac{254797}{125243-29278} = 2.66$	$\frac{93351}{121710-10479} = 0.84$

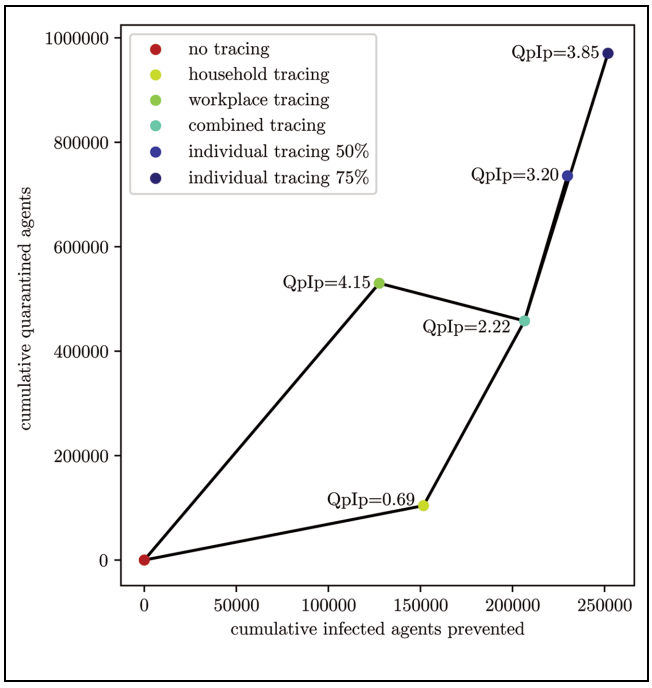

Figure 6 Cumulative quarantined agents plotted against cumulative infected agents prevented by tracing compared with the no-tracing scenario. The valued displayed corresponds to the defined cost measure quarantined per infection prevented (*QpIp*). Lines illustrate that the strategy to the top right is based on the strategy to the bottom left and can be labeled as "stricter." For example, the combined tracing strategy is based on the household and the workplace tracing.

infectious persons dominates the system, many new infections will increase the number of persons in preventive isolation and therefore the economic costs. Increasing the strictness of the tracing measure will contribute to make the right feedback loop dominant and contain the disease. Yet, it directly increases the number of quarantined people at first. If applied in a successful containment strategy, both the infected and the preventively isolated people can be kept on a low level.

The model results nicely display the impact of this feedback. While peaking the increasing case numbers in May and June requires many preventive quarantined persons, the low case numbers in the well-contained disease from July to November reduce the costs for the strategy. Consequently, the model results support the idea that tracing is much more efficient when case numbers are low, not only due to limited tracing resources. Hence, a strict contact-tracing policy is costly in the first place but pays off in the long run.

In general, the findings of this work match the experience of countries that already implemented large-scale and precise contact tracing such as Singapore or South Korea[31,32] and had great success with the strategy. However, both countries have already experienced that pure contact tracing alone is not sufficient to fully contain the disease.

Moreover, recent results from Austria contribute to the validation process of this study. While the country managed to contain the case numbers during the summer months, a second wave started to become eminent in October when the case numbers started growing with R_{eff} 1.2. On October 20, the case numbers hit 1500 new confirmed cases per day, and the ascend almost instantaneously steepened to a higher level of R_{eff} 1.4.[33] This increase by 0.2 came as a surprise to Austrian decision makers, since there was neither any policy, holiday, nor weather change involved that might have explained it. Yet, a closer look at the cluster data[33] indicated that the Austrian contact-tracing regime, although never

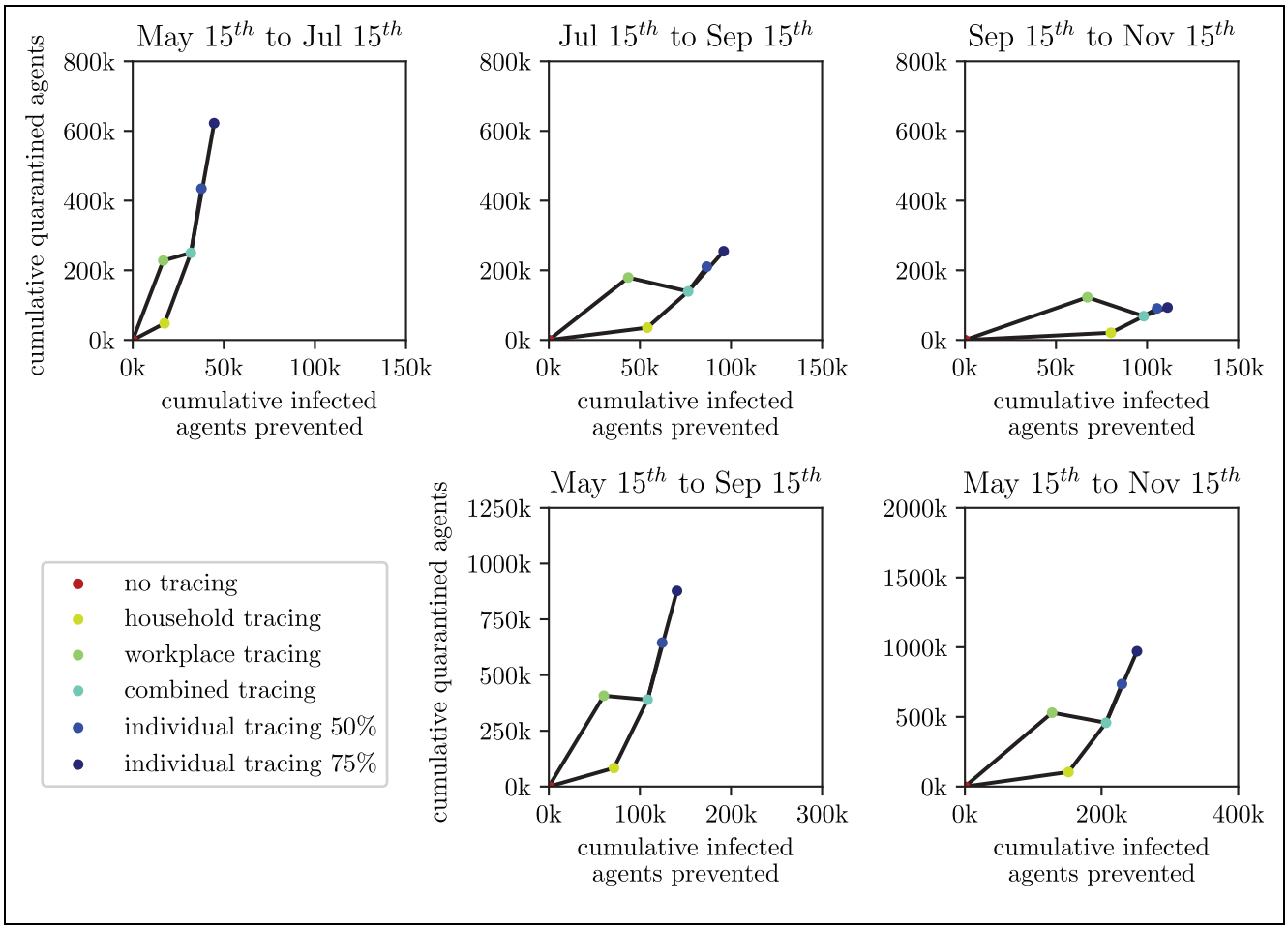

Figure 7 Analogous curves to Figure 6, yet the cumulative cases are not evaluated for the whole period of May 15 to November 15 but for 3 subintervals of 2 mo each. The lines illustrate that the strategy to the top right is based on the strategy to the bottom left and can be labeled as "stricter."

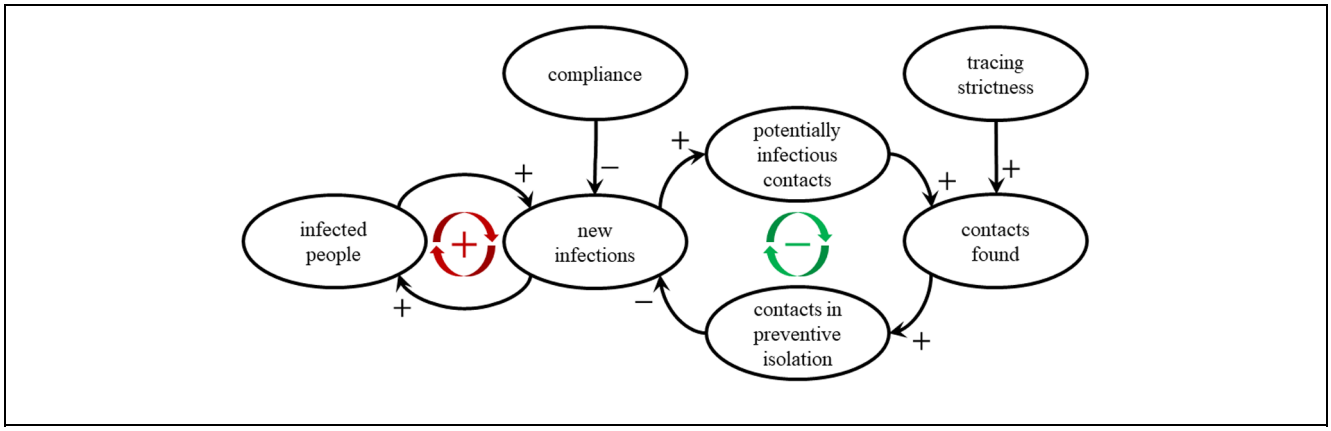

Figure 8 Causal loop diagram of relevant system components with respect to tracing measures. The more dominant the feedback loop on the left-hand side, the more potentially infectious contact partners need to be isolated to contain the disease.

officially confirmed, might have run out of resources at this time.

In summary, the model indicates that all tracing measures can supplement a small amount of infectivity reduction and can therefore play a role in a successful containment strategy. This strategy is particularly valuable because it does not require additional behavior restrictions from the common public but focuses only a part of the contact network of positively tested persons. The related costs can be measured in preventively quarantined persons and are reduced not only by accurate tracing but also by low case numbers.

Limitations

We distinguish between limitations of the study design, limitations of the simulation results, and limitations of the model as a decision support tool.

First, the study design does not include any testing of detected contact persons. Finding additional positive cases within contact partners would increase the capabilities of the strategy to enhance tracing to the next generation and would slightly increase the efficacy of the policy. Moreover, the study does not specifically regard sensitivity or specificity of the test that is used to determine the index cases for contact tracing. Test sensitivity is implicitly depicted in the general detection probability of COVID-19 cases. Test specificity is not regarded at all, which was already analyzed in the "Discussion" section. Moreover, the duration between the start of infectivity and the receiving of the test result is parametrized for typical PCR tests and might be different for antigen tests or others. The reader is referred to the parameter tables in the Appendix for more information.

The model results are, as all simulation outcomes, limited by modeling and data uncertainty: many disease parameters of the novel coronavirus are still unknown and will surely improve in the future because of increasing availability of data. In particular, the model suffers from the reporting bias of the calibration data. The constantly changing and limited availability of tests in the first months of the disease might cause the data to estimate the real epidemiology falsely.

Moreover, the parameters and the modeling assumptions for the tracing strategies are based on expert opinions. Consequently, the tracing algorithm is modeled in an oversimplified form and cannot validly depict the actual work of professional contract tracers. Similarly, the strategy for location closure is implemented in an extremely strict fashion, since the occurrence of only 1 positive case would cause preventive closure of the entire workplace. In reality, more balanced solutions would probably be implemented, wherein the measure is applied after a higher threshold is reached (e.g., multiple positive tested employees) or for certain parts of the workplace (e.g., individual offices).

Interpreted as a decision support tool, the model is primarily limited by comparably long computation times and fundamental simplifications made during the modeling process. The prior is caused by the problem that the model cannot be scaled down and always requires simulation with the full population of the country. Thus, a huge number of agents (about 9 million for Austria) leads to long computation times, and the necessity of Monte Carlo simulation for flattening of stochastic results increases the time required to increase the simulation output even more. Consequently, the simulation's capabilities of dealing with multivariate calibration problems are limited, and the model is capable, yet unhandy, of generating short-term prognoses.

Conclusion

We presented an agent-based simulation model that is not only capable of simulating epidemics but can also be used to evaluate and compare different containment strategies. In addition to classic lockdown interventions such as closure of schools or workplaces, the model can also be used to compare different tracing policies, which makes it unique and powerful.

Hereby, we also displayed the limits of classical cohort models, as comparable scenarios would not be feasible with aggregated modeling approaches. By aggregating individual contacts into global contact rates, individual contact chains are lost, and tracing cannot be modeled.

For our policy question on tracing, we investigated 6 tracing strategies for 3 compliance scenarios regarding a second outbreak of COVID-19 in Austria. They allowed us to simulate and quantify the impact of different tracing policies and draw conclusions about tracing in general.

The results demonstrate that tracing of potentially infectious contacts and subsequent isolation of affected persons is an effective measure to slow the spread of SARS-CoV-2 and that there are more and less restrictive ways to do so. The model results display that a well contained disease also reduces the socioeconomic costs for tracing in terms of fewer quarantined persons. Consequently, the model results recommend strict and accurate tracing strategies in favor of rigorous preventive closure of locations such as workplaces, which cause many unnecessarily quarantined healthy persons. However, the model results also show that tracing in any variant,

although effective, can play a only minor role in disease containment.

Evaluating the effectiveness of tracing policies is only one of many features of this advanced ABM. Although the model has limitations, it is a well-founded basis for COVID-19–related decision support, as it can include complicated model logic as well as diverse and high-resolution data. Hence, we plan to extend our policy comparisons started in this study in the future by direct comparison of other interventions, such as a more advanced testing regime or the introduction of a vaccine.

Authors' Note

Partial results of this work have been presented at the following:

- Webinar of the Austrian Association for Public Health: Martin Bicher, "Mathematik als wichtige Public Health Disziplin: Modellbildung und Simulation als Eckpfeiler im Kampf gegen COVID-19"
- X-Europe joint data-science webinar: Martin Bicher, "Modelling the Spread of SARS-CoV-2: How Reliable Are Simulated Forecasts?"
- Keynote, ASIM SST 2020, Niki Popper and Martin Bicher, "Simulation-Based Decision Support: The COVID19 Crisis from a Modeller's Perspective"

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Supplemental Material

Supplementary material for this article is available on the *Medical Decision Making* website at http://journals.sagepub.com/home/mdm.

Note

i. This number corresponds to the actual state of the confirmed cases on the specified date at the specified time. Because of a reporting bias, this number is subject to constant changes and will probably increase in the future.

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