The Potential of Digital Symptom-based Screening to Reduce the Transmission of SARS-CoV-2: a Modelling Study

Jan Multmeier, Maryam Montazeri, Nicola Vona, François Bergey, Alicia Mehl, Andreas Gilsdorf

Submitted to: Journal of Medical Internet Research
on: June 11, 2021

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Jan Multmeier[1] PhD; Maryam Montazeri[1] PhD; Nicola Vona[1] PhD; François Bergey[1] MSc; Alicia Mehl[1] MSc; Andreas Gilsdorf[1] MD

[1]Ada Health GmbH Berlin DE

Corresponding Author:
Jan Multmeier PhD
Ada Health GmbH
Karl-Liebknecht-Strasse 1
Berlin
DE

Abstract

Background: Early efforts to control the COVID-19 pandemic have been focused on Non-Pharmaceutical Interventions (NPIs) in the absence of effective treatments or sufficient vaccine supply. While retrospective analyses and modeling studies confirmed that severe restrictions of social contacts, i.e., lockdowns, are most effective in reducing transmission of SARS-CoV-2, they incur large economic costs and mental health risks. Earlier detection of cases has also been proposed as an effective method of control, but studies have so far only considered enhanced laboratory testing. Digital applications have been developed which aim to identify possible cases of COVID-19 based on reported symptoms and risk factors.

Objective: The aim of this study is to explore the effects of digital screening applications for COVID-19 on the transmission of SARS-CoV-2.

Methods: Using an established epidemiological Susceptible-Exposed-Infectious-Recovered (SEIR) model for infectious disease transmission, we simulate the transmission of SARS-CoV-2 in Germany, the UK, and the USA for 366 days after the virus was introduced in the population. We study 4 scenarios: 1) no interventions (base case), 2) symptom-based self-isolation after consulting healthcare providers, 3) self-isolation using digital screening applications, and 4) severe social contact limitations (lockdown). We included sensitivity analyses for different ratios of infectiousness of pre-symptomatic cases compared to symptomatic cases, and different rates of adoption of digital screening tools.

Results: Without any intervention, 74% of the German population would be infected with SARS-CoV-2 within the simulation period (UK: 76%, USA: 77%). Self-isolation of symptomatic cases would already slow the spread of the virus significantly and lead to only 18% of the German population being infected (UK: 17%, USA: 17%). Using a digital application could further reduce the infected population to 10% (UK: 9%, USA: 9%), compared to 3% under lockdown conditions. While the effectiveness of digital screening applications varies with the adoption rate, even a low adoption rate could significantly reduce transmission. In the case that pre-symptomatic cases are less infectious than symptomatic cases, the overall proportion of infected individuals in the population decreases, and the effectiveness of different interventions converges.

Conclusions: Digital symptom-based screening tools can substantially impact the transmission of SARS-CoV-2 and might be a viable element in strategies to control COVID-19 through NPIs.

(JMIR Preprints 11/06/2021:31139)
DOI: https://doi.org/10.2196/preprints.31139

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Jan Multmeier, PhD[1], Maryam Montazeri, PhD[1], Nicola Vona, PhD[1], François Bergey, MSc[1], Alicia Mehl, MSc[1], Andreas Gilsdorf, MD[1]

1 - Ada Health GmbH, Karl-Liebknecht-Str. 1, 10178 Berlin, Germany

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Early efforts to control the COVID-19 pandemic have been focused on Non-Pharmaceutical Interventions (NPIs) in the absence of effective treatments or sufficient vaccine supply. While retrospective analyses and modeling studies confirmed that severe restrictions of social contacts, i.e., lockdowns, are most effective in reducing transmission of SARS-CoV-2, they incur large economic costs and mental health risks. Earlier detection of cases has also been proposed as an effective method of control, but studies have so far only considered enhanced laboratory testing. Digital applications have been developed which aim to identify possible cases of COVID-19 based on reported symptoms and risk factors.

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Conclusion

Digital symptom-based screening tools can substantially impact the transmission of SARS-CoV-2 and might be a viable element in strategies to control COVID-19 through NPIs.

Introduction

The global spread of the novel coronavirus SARS-CoV-2 resulted in large numbers of cases of COVID-19 and deaths across all affected regions. As of May 2021, the World Health Organization reported over 144 million cases across 237 countries[1]. In an early effort to contain the spread of SARS-CoV-2 and in the absence of an effective treatment or timely availability of vaccines, countries have implemented a range of non-pharmaceutical interventions (NPIs). Those NPIs aim to a) reduce the infectiousness of cases (e.g., wearing face masks, observing cough etiquette), b) reduce the contact rate of individuals in the population (e.g., school closures, banning mass events and gatherings, or social distancing regulations), c) identify transmission chains (e.g., contact tracing), and d) detect cases early (e.g., rapid antigen testing, temperature control). Practically, all NPIs aim to reduce the effective reproduction number (R) of the virus below 1 or to a level where the number of cases does not overwhelm healthcare system resources. In an analysis on the effectiveness of NPIs in Europe, Flaxman et al.[2] concluded that all studied NPIs (banning public events, encouraging social distancing, school and university closures, case-based isolation, timing of first government intervention, and lockdown) together effectively reduced R below 1, with lockdowns singularly reducing R by 81%. A modeling study by Davies et al.[3] found that lockdowns were the only NPI to reduce R below 1, and that intensive interventions with lockdown periods would become necessary for large proportions of the year 2021 to prevent healthcare demand exceeding availability. Among the NPIs Davies et al. examined, self-isolation of symptomatic cases has been found to significantly decrease the total number of cases and deaths and to delay the time to the maximum number of weekly cases in a 23-month window, compared to no intervention. Given that the viral load of an infected individual is highest around the time of symptom onset[4–7], detecting cases early has a substantial impact on the effectiveness of self-isolation. For example, early detection of symptomatic cases in China has been estimated to reduce transmission by 35%[8]. However, examination and testing of symptomatic cases in healthcare facilities can lead to delayed self-isolation due to limitations in healthcare resources (e.g., nurses, physicians, diagnostic tests, laboratory capacity) or a low perceived acuity of symptoms. A study in Brazil using diagnostic test panel data found an average time between reported onset of symptoms and testing of 10.2 days[9]. Self-isolation only after receiving a positive test result would be rendered ineffective. As COVID-19 presents with a variety of symptoms (e.g., fever, cough, difficulty breathing, sore throat, nasal congestion, anosmia) [10], differentiating a SARS-CoV-2 induced case of COVID-19 from cases of flu or other coronaviruses is challenging. However, a number of symptom-based digital screening applications have been developed to provide medical guidance to people experiencing COVID-19-related symptoms[11–16]. These digital tools could potentially reduce the delay from the onset of symptoms to self-isolation, which may reduce the transmission of SARS-CoV-2 in the population and thereby help to mitigate capacity constraints of the healthcare systems. Especially in lower-resourced contexts with reduced access to vaccines or testing capacity, or with emergent SARS-CoV-2 strains less receptive to existing vaccines, digital screening applications could contribute to allocating limited health resources efficiently and reducing transmission.

While the role of diagnostic testing has been explored in previous research, the potential contribution of a symptom-based COVID-19 digital screening application to reducing transmission has not been explored. The present study aims to close this gap.

Methods

In this study, we investigated the effect of using a digital COVID-19 screening application on the

transmission of SARS-CoV-2. For this purpose, we adapted an established dynamic epidemiological model of disease transmission[17] and considered four general scenarios:

A. a base case without any interventions (base case),
B. self-isolation of symptomatic cases after consultation with a healthcare professional (self-isolation with healthcare use),
C. self-isolation of symptomatic cases after self-assessment by a COVID-19 screening application (self-isolation with screening application use), and
D. strict social contact limitations (lockdown).

We simulated these four scenarios in three different populations: Germany, the UK, and the USA. Data regarding the age distribution was obtained from the population data query of the United Nations (UN) website[18] (see supplementary table 1). As a starting point for our simulation, we considered 0.01% of the population to be infected and simulated the transmission for a time period of 366 days.

In accordance with two studies from Prem et al[17,19] , we applied country-specific contact patterns to model the contact restrictions in each scenario through generating synthetic contact matrices. The following paragraphs describe the contact matrices in each scenario, the model, and the assumptions we used.

Contact matrices

Base case

Prem et al[19] calculate social contacts for four specific locations (household, school, work, and other locations) across 16 age groups in 152 countries. The overall contact rate for each individual is given by the sum of interactions of their respective age group with all other age groups across the four locations. The contact matrix for the *base case* is referred to as C^b in the subsequent equations.

Self-isolation scenarios

We assumed that self-isolation leads to a 50% reduction in contacts in the household and complete reduction of contacts at schools, the workplace, and other locations. The contact matrix for self-isolation is referred to as C^{is}.

Lockdown

We assumed that in the case of strict contact limitations, contacts in the household remain the same as in the base scenario. Due to school and university closure, contacts in schools are set to zero. For the workplace and other locations, we adopted the strongest restriction in contacts reported in Prem et al.[17], i.e., 10% of the base case contacts. The contact matrix for the *lockdown scenario* is denoted by C^{sd} in our equations. Symptomatic individuals will also self-isolate in this scenario, reducing the contacts in the household by 50%.

The modifications to assumed contact rates by location for each scenario are summarized in Table 1.

Table 1: Contact restrictions by location for each scenario

Contact matrices per scenario	locations			
	household	school	work	other locations

C^{b}	100%	100%	100%	100%
C^{sd}	100%	0%	10%	10%
C^{is}	50%	0%	0%	0%

Model structure

We used a modified Susceptible-Exposed-Infectious-Recovered (SEIR) model (Figure 1; see also Table 2 for the numerical values of the parameters) to simulate the transmission of SARS-CoV-2 in a population, where each individual at time *t* is either susceptible to infection, exposed to the virus, infectious, or recovered. Figure 1 shows several scenarios that we considered in our model.

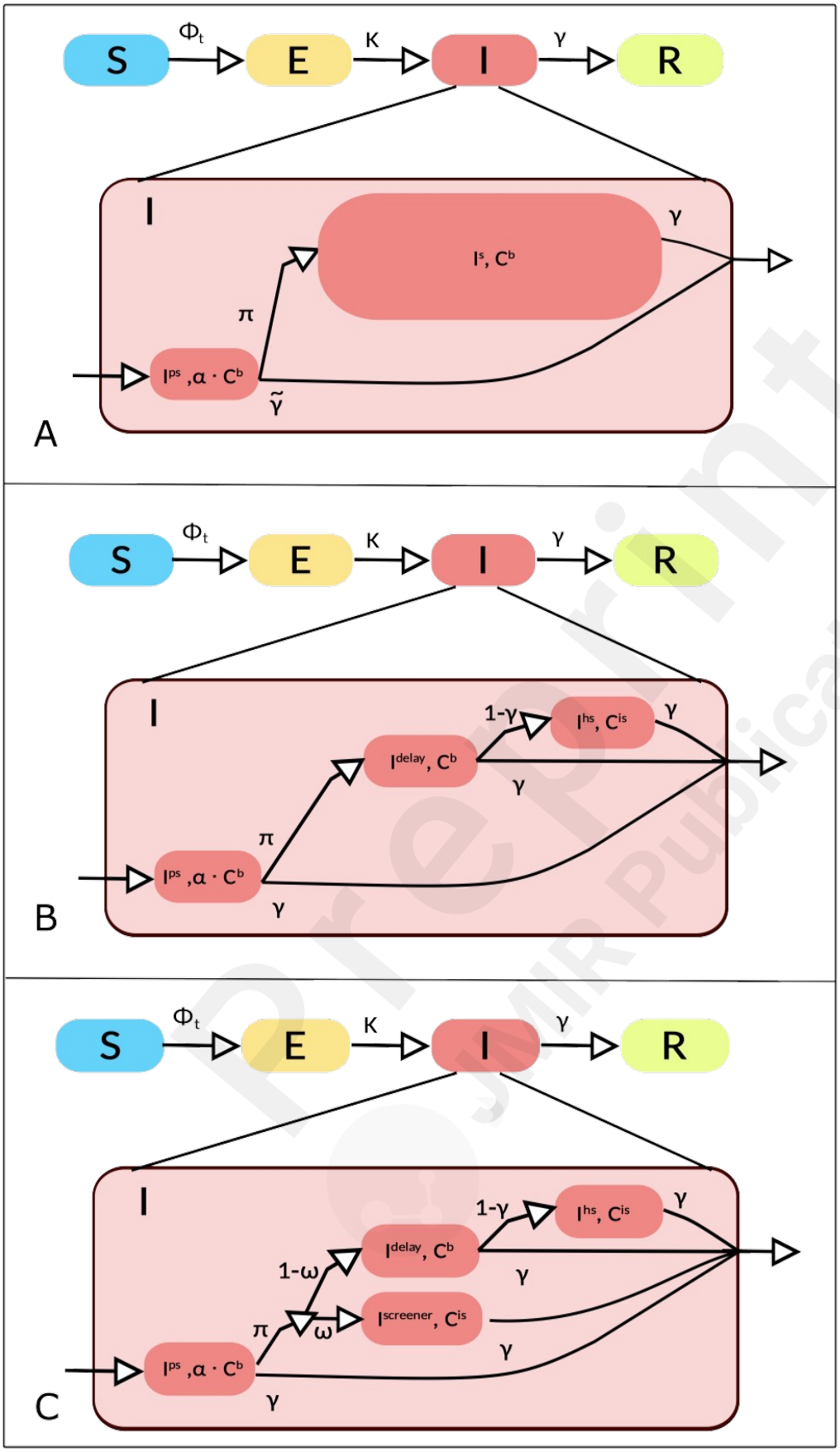

Figure 1: Structure of the SEIR model, with A) the base case of no interventions and pre-symptomatic transmission, B) self-isolation of symptomatic cases with delay, and C) immediate self-isolation of symptomatic cases when using a digital screening application or delayed self-isolation

otherwise.

We start with the model in Figure 1-A. We denote by *S(t)*, *E(t)*, *I(t)* and *R(t)* the number of susceptible, exposed, infectious, and recovered individuals, respectively, for each of the 16 age groups of the contact matrices. To account for pre-symptomatic transmission, we split the infectious population into a pre-symptomatic and a symptomatic compartment

$$I(t)=I^{ps}(t)+I^{s}(t). \qquad \textbf{eq.1}$$

Correspondingly, we split the average duration of incubation d_{inc} between exposure and symptom onset into a non-infectious latency d_{lat} and an infectious pre-symptomatic phase d_{ps},

$$d_{inc}=d_{lat}+d_{ps}. \qquad \textbf{eq.2}$$

Then, the average duration of infectiousness is

$$d_{inf}=d_{ps}+d_{s}, \qquad \textbf{eq.3}$$

where d_s is the average duration of the symptomatic phase.
The model dynamics are governed by the equations

$$S(t+1)=(1-\Phi(t))S(t), \qquad \textbf{eq.4}$$
$$E(t+1)=\Phi(t)S(t)+(1-K)E(t), \qquad \textbf{eq.5}$$
$$I(t+1)=KE(t)+(1-\gamma)I(t), \qquad \textbf{eq.6}$$
$$R(t+1)=\gamma I(t)+R(t), \qquad \textbf{eq.7}$$

and accounting also for the internal pre-symptomatic and symptomatic compartments

$$I^{ps}(t+1)=KE(t)+(1-\gamma-\pi)I^{ps}(t), \qquad \textbf{eq.8}$$
$$I^{s}(t+1)=\pi I^{ps}(t)+(1-\gamma)I^{s}(t). \qquad \textbf{eq.9}$$

The parameter $K=1/d_{lat}$ expresses the rate at which the exposed population converts to the infectious state, the parameter $\gamma=1/d_{inf}$ is the rate at which the infectious population recovers, while π is the rate at which the pre-symptomatic population transitions to the symptomatic phase, and is such that

$$\gamma+\pi=\frac{1}{d_{ps}}. \qquad \textbf{eq.10}$$

Finally, $\Phi(t)$ expresses the rate at which the susceptible population becomes infected, and is related to the size of the infectious population through the contact matrices

$$\Phi(t)=\alpha\beta C^{ps}I^{ps}(t)+\beta C^{s}I^{s}(t) \qquad \textbf{eq. 11}$$
$$\beta=\frac{R_0}{Nd_{inf}}, \qquad \textbf{eq. 12}$$

where β is the transmission rate[17], R_0 is the basic reproduction number[17], N is the size of the overall population, while α is a factor expressing the reduced infectiousness of a presymptomatic case as compared to a symptomatic case[17]. The role that children play in terms of susceptibility to

infection, transmission, and severity of disease is currently under debate[20–23]. Given the lack of consensus at present, we have not incorporated age-dependencies into the transmission rate β.

The model of Figure 1-A represents the baseline of the infection without any interventions, therefore we set in this case $C^{ps}=C^{s}=C^{b}$.

Next, we consider a self-isolation scenario (Figure 1-B), in which symptomatic cases self-isolate after consulting with a healthcare professional, which we assume to happen on average one day after symptom onset. We therefore split the compartment I^{s} into the subcompartments I^{delay} of the symptomatic individuals waiting to consult with a healthcare professional, and I^{hc} of the symptomatic individuals under self-isolation after the consult. Then,

$$I(t)=I^{ps}(t)+I^{delay}(t)+I^{hc}(t), \quad \textbf{eq.13}$$
$$I^{ps}(t+1)=KE(t)+(1-\gamma-\pi)I^{ps}(t), \quad \textbf{eq.14}$$
$$I^{delay}(t+1)=\pi I^{ps}(t), \quad \textbf{eq.15}$$
$$I^{hc}(t+1)=(1-\gamma)I^{delay}(t)+(1-\gamma)I^{hc}(t), \quad \textbf{eq.16}$$
$$\Phi(t)=\alpha\beta C^{ps}I^{ps}(t)+\beta C^{delay}I^{delay}(t)+\beta C^{hc}I^{hc}(t). \quad \textbf{eq.17}$$

In this scenario, we set

$$C^{ps}=C^{delay}=C^{b}, \quad \textbf{eq.18}$$
$$C^{hc}=C^{is}. \quad \textbf{eq.19}$$

We now add the possibility for a symptomatic individual to make use of a digital COVID-19 screening application to decide to self-isolate immediately at symptom onset without waiting to consult with a healthcare professional to the model (Figure 1-C). In this scenario, when transitioning out of the pre-symptomatic phase, each individual will use the screener and self-isolate immediately with probability ω, otherwise waiting to consult with a healthcare professional. We then get the equations

$$I(t)=I^{ps}(t)+I^{screener}(t)+I^{delay}(t)+I^{hc}(t), \quad \textbf{eq.20}$$
$$I^{ps}(t+1)=KE(t)+(1-\gamma-\pi)I^{ps}(t), \quad \textbf{eq.21}$$
$$I^{screener}(t+1)=\pi\omega I^{ps}(t)+(1-\gamma)I^{screener}, \quad \textbf{eq.22}$$
$$I^{delay}(t+1)=\pi(1-\omega)I^{ps}(t), \quad \textbf{eq.23}$$
$$I^{hc}(t+1)=(1-\gamma)I^{delay}(t)+(1-\gamma)I^{hc}(t), \quad \textbf{eq.24}$$
$$\Phi(t)=\alpha\beta C^{ps}I^{ps}(t)+\beta C^{screener}I^{screener}(t)+\beta C^{delay}I^{delay}(t)+\beta C^{hc}I^{hc}(t). \quad \textbf{eq.25}$$

In this scenario, we set

$$C^{ps}=C^{delay}=C^{b}, \quad \textbf{eq.26}$$
$$C^{hc}=C^{screener}=C^{is}, \quad \textbf{eq.27}$$

and we used the values 0.45, 0.75, and 1 for ω as sensitivity checks.
The contribution of pre-symptomatic individuals to the transmission dynamics of SARS-CoV-2 is not completely clear[5,7,24–26]. To reflect the fact that a higher contribution of pre-symptomatic cases to the transmission of SARS-CoV-2 would diminish the potential effect of symptom-based screening, we systematically varied the relative infectiousness α of pre-symptomatic cases between 25% and 100% of the infectiousness of symptomatic cases.

Finally, we consider the lockdown scenario, in which social contacts in the population are severely reduced and symptomatic cases self-isolate after consulting with a healthcare professional. This scenario is realized by the model in Figure 1-B by setting

$$C^{ps} = C^{delay} = C^{sd}, \quad \textbf{eq.28}$$
$$C^{hc} = C^{is}. \quad \textbf{eq.30}$$

The numerical values of all model parameters are reported in Table 2.

Table 2: Model parameters

Parameter Notation	Parameter Definition	Parameter Value(s)	Reference/Source
d_{inc}	Duration of incubation between exposure and symptom onset	6.4	Prem et al.[17]
d_{ps}	Duration of pre-symptomatic phase	2.5	Prem et al.[17]
d_s	Duration of symptomatic phase	7	Prem et al.[17]
R_0	Basic reproduction number	2.6	Prem et al.[17]
N	Size of the overall population	DE: 83.5 Million UK: 67.9 Million USA: 331,1 Million	UN[18]
α	Infectiousness ratio of presymptomatic compared to symptomatic	0.25, 0.5, 0.75, 1	modelling assumption with sensitivity analysis
ω	Percentage of digital symptom assessment users	45%,75%,100%	modelling assumption with sensitivity analysis
T	Days after disease initiation, restriction are applied	60	modelling assumption

Assumptions

As with every model, our approach makes assumptions that either are inherent to the modeling method or are used to simplify the calculations:

1. The COVID-19 screener and healthcare providers are 100% sensitive in detecting cases of COVID-19
2. Individuals perfectly adhere to the recommendation to self-isolate immediately
3. Interventions are installed 60 days after the first introduction of COVID-19 to the population, and the transmission is modelled over a course of 366 days
4. Individuals will consult with a healthcare provider and self-isolate one day after symptom onset, whereas individuals who use the digital screening application self-isolate on the same day as symptom onset
5. Each simulated country population is closed, i.e., there are no births, deaths, or migration
6. Individuals who recovered are immune and do not become susceptible to re-infection

Results

In Table 3**,** we report the overall proportion of the respective population infected in the 366 days of the simulation. The results are reported for different values of α, which represents the relative infectiousness of pre-symptomatic cases compared to symptomatic cases. In the case of equal infectiousness ($\alpha=1$), 73.6% of the German population (UK: 76.2%, USA: 76.7%) would be infected in the absence of interventions (base case). Introducing isolation of symptomatic cases with healthcare use already leads to substantial reduction of transmission, with only 18.3% (UK: 17.3%, USA: 16.6%) of the population being infected. Using a digital COVID-19 screening application when experiencing symptoms could further reduce the proportion of infected individuals to 9.8% (UK: 9.1%, USA: 8.5%), a relative reduction of cases by 47% (UK: 48%, USA: 49%), in the best case where digital screening applications are adopted universally, compared to self-isolation with healthcare use. If pre-symptomatic cases are only 25% as infectious as symptomatic cases, the overall proportion of infected individuals decreases in the base case (Germany: 63.3%, UK: 65.8%, USA: 66.0%), and so does the relative effectiveness of a digital screening application (Germany: 18%, UK: 16%, USA: 25%). Assuming only partial adoption of digital screening applications reduces their effectiveness, although the size of the reduction is low overall (4 percentage points in Germany, 1 in the UK and 3.6 in the USA) and the effectiveness is higher in all scenarios compared to self-isolation with healthcare use alone. Lockdowns with corresponding strict contact limitations are most effective in preventing transmission, with only 3.28-0.52% of the German population infected in the simulation period (UK: 3.13-0.89%, USA: 2.96-0.47%).

Table 3: Proportion of the population infected by scenario and country

Proportion of infected population after 366 days (in %)												
		Germany				United Kingdom				United States			
		Infectiousness of pre-symptomatic cases compared to symptomatic cases (α)											
Scenario		**0.25**	**0.5**	**0.75**	**1**	**0.25**	**0.5**	**0.75**	**1**	**0.25**	**0.5**	**0.75**	**1**
Base case		63.31	67.34	70.72	73.58	65.75	69.89	73.32	76.20	66.02	70.25	73.75	76.66
self-isolation with healthcare use		0.79	1.95	6.33	18.31	0.74	1.82	5.80	17.30	0.71	1.71	5.40	16.64
self-isolation with use of digital screening application	***45% adoption***	0.71	1.62	4.58	13.75	0.67	1.52	4.21	12.80	0.64	1.44	3.93	12.16
	75% adoption	0.67	1.48	3.89	11.37	0.64	1.40	3.61	10.55	0.61	1.32	3.37	9.96
	100% adoption	0.65	1.39	3.47	9.79	0.62	1.32	3.23	9.08	0.59	1.24	3.03	8.53
Lockdown		0.52	0.93	1.72	3.28	0.50	0.89	1.65	3.13	0.47	0.84	1.56	2.96

As **Figure 2** reveals, all examined NPIs reduce the daily number of infectious cases significantly compared to the base case. Without any intervention, at the peak of transmission, 13.1% of the German population would be active infected cases (UK: 13.5%, USA: 13.4%). Case isolation after consulting healthcare professionals (Germany: 1.6%, UK: 1.5%, USA: 1.5%), or using a digital screening tool (Germany: 1.4-1.3%, UK: 1.4-1.3%, USA: 1.3-1.2%) would substantially reduce this proportion. Lockdowns lead to the lowest proportion of daily active cases (Germany: 1.1%, UK: 1.1%, USA: 1.0%).

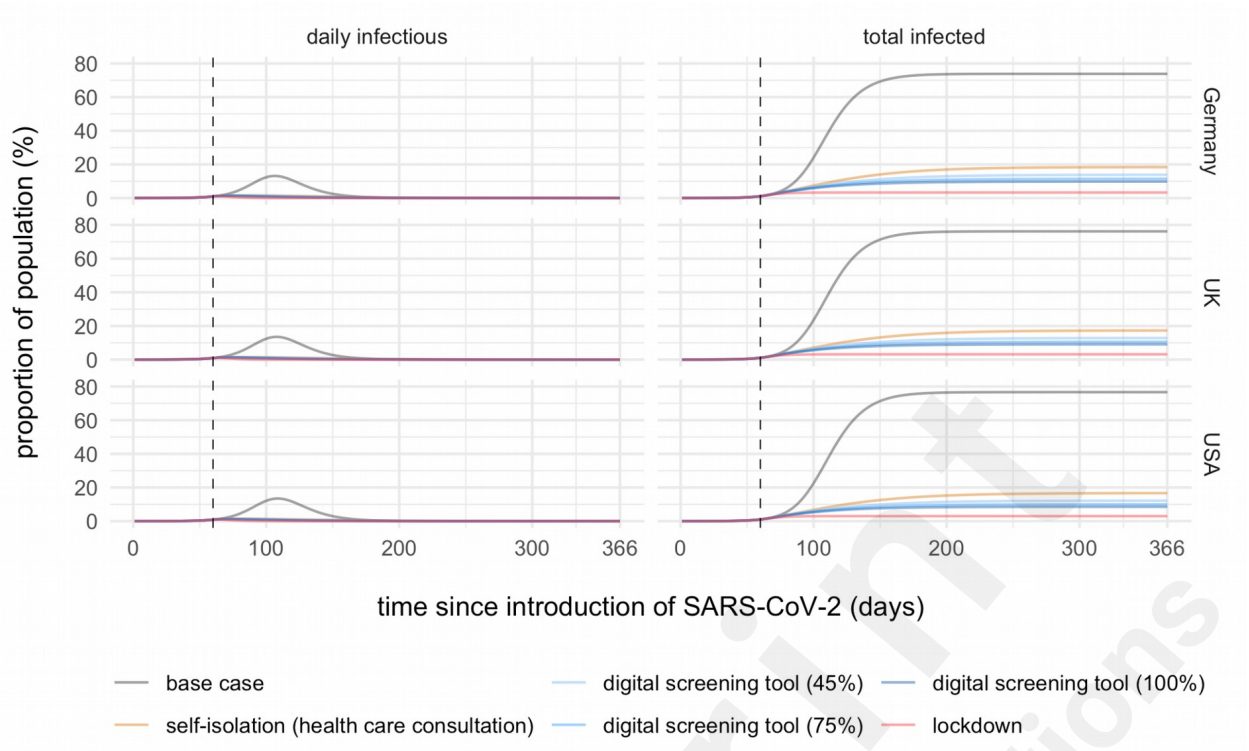

Figure 2: daily infectious (left) and total cumulative number of infected cases (right) for Germany (top), the UK (middle) and the USA (bottom) for different modelling scenarios. The dashed line indicates the introduction of NPI 60 days after the introduction of SARS-CoV-2 to the population.

Discussion

In this study, we investigated the potential of a digital screening application in reducing the transmission of SARS-CoV-2 in three populations: Germany, the UK, and the US. For this purpose, we simulated the propagation of the disease in four main scenarios: a) in the absence of any interventions, b) self-isolation of symptomatic cases after consulting healthcare providers, c) self-isolation of symptomatic cases after using a digital screening application, and d) lockdown with severe restrictions of social contacts. Our study showed that in absence of any interventions, SARS-CoV-2 would infect the majority of the populations within a year, until the proportion of infected individuals approaches the “herd immunity” threshold, which can be calculated as 62%[27] with our chosen R_0 value of 2.6.

Introducing self-isolation after experiencing symptoms and consulting with a healthcare provider drastically reduced the transmission of SARS-CoV-2. While the magnitude of this effect may be surprising, we believe it is driven by two facts: first, our definition of “symptomatic” cases includes symptoms that may not prompt a case to consult with healthcare providers regarding a current infection with SARS-CoV-2. We adopted the probability of being symptomatic when infected with SARS-CoV-2 from Prem et al., who in turn cite Bi et al.[28]. In their study, Bi et al. also included mild symptoms (e.g., fatigue, runny nose, headache) when reporting the proportion of symptomatic cases. Second, we assume that all symptomatic cases infected with SARS-CoV-2 are identified correctly at the healthcare provider, and that all affected individuals adhere to the self-isolation requirement. Thus, the effect presented here represents the maximum achievable effect rather than a realistic assessment.

The assumed time savings of one day from symptom onset to self-isolation again substantially reduced the observed number of cases over the simulation period. This demonstrates the importance of early isolation of cases after the onset of symptoms. Similar simulation studies[8,29] have shown that early detection and strict case isolation can contribute substantially to reduce the transmission of

SARS-CoV-2. The effect we observed for Germany with adherence digital screening application use and equal infectiousness of symptomatic and pre-symptomatic cases was comparable to that Liu et al.[8], who described a 35% reduction in cases through accelerated case isolation.
In accordance with previous studies[2,30–32], we showed that lockdowns, i.e., severe limitations of social contact in the population, are most effective in reducing the transmission of SARS-CoV-2. Symptom-based screening, either through healthcare professionals or a digital screening application, can significantly reduce transmission and come without the burden of lockdowns to personal health[33–36] and freedom, and prosperity of the personal and national economy[37,38]. While vaccines will become more available in the near future and severe restrictions of social contacts a last resort to control the pandemic, other NPIs can complement immunization efforts to keep the transmission of SARS-CoV-2 within manageable limits. Especially in contexts of restricted vaccine availability or reduced vaccine effectiveness, NPIs will be essential to mitigate the effects of COVID-19.

To put the results of our analysis in context, we compared the estimation generated by the epidemiological model to the real-world pandemic surveillance data of the Our World in Data research group[39]. Using the same time parameters, in the year after 0.01% of the respective populations were infected, 3.4% of the German (UK: 6.5%, USA: 9.3%) populations have been infected, which corresponds approximately to the effects observed under lockdown conditions. During the course of the pandemic, various control and mitigation policies have been in place, which our model did not include, making the comparison between countries in our model and reality challenging.

Limitations

The results of this study, like those of all modelling studies, are limited in their generalizability by constraints due to the chosen methodology, scope, and simplifying assumptions.

The main limitation of this study is our assumption of perfect sensitivity of healthcare providers and digital screening tools for detecting an infection with SARS-CoV-2. In reality, neither PCR-based nor antigen tests provide perfect sensitivity[40,41]. While a recent comparison study of ten different digital screening applications (Munsch et al.[42]) found that some of the tested applications had near perfect sensitivity based on artificial case vignettes, the diagnostic accuracy in real cases and by real users remains to be evaluated (see Millen et al.[43] for a methodological critique).

Second, we assume absolute adherence to a) consulting healthcare providers or digital screening applications when experiencing symptoms, and b) self-isolation for the remainder of the infectiousness period, or c) to the lockdown measures implemented. Smith et al[44] showed that in the UK, only 31.3% of people reported not leaving home after developing symptoms, which would undermine any effort in reducing transmission by isolating symptomatic cases.

Third, the interventions modelled were limited to those aimed at identifying symptomatic cases and NPI. We did not include the effects of vaccinations or antigen or PCR-based tests for SARS-CoV-2, and also did not model combinations of interventions.

Fourth, we focused on the proportion of the population that is infected with SARS-CoV-2 over the simulation period and have shown that all interventions are effective in reducing the transmission compared to the base case. Whether the reductions in cases we observed prevents healthcare resources from being depleted was not the focus of this study and should be evaluated in subsequent publications, using a modeling scenario that focuses on close representation of reality.

Fifth, our model used transmission parameters observed with the first strain of SARS-CoV-2 in the early phase of the pandemic. In the meantime, mutations of the virus have led to other variants that exhibit different transmission parameters, e.g., lineage B.1.1.7 discovered in England was found to be significantly more transmissible than the first strain[45]. It is likely that the effects observed would increase given a higher transmissibility and thus a higher chance that one case infects others during the assumed one day delay of self-isolation, but the precise effect needs to be estimated with adapted parameters of our model.

And finally, all interventions have unintended consequences that were not part of our assessment. Lacking specificity of screening tools or tests would lead to an excessive number of people under (unnecessary) self-isolation, and prolonged periods of lockdowns carry high costs with regards to mental health and economic stability.
As the scope of this study was to evaluate the potential of digital screening applications compared to diagnosis by a healthcare provider and not to evaluate real performance of available solutions, testing the maximum achievable effectiveness was more appropriate than testing a scenario that conforms as closely as possible to reality. Future studies assessing the effectiveness of the interventions presented here in real world settings need to account for these limitations.

Conclusion

Even a small amount of time saved between infectiousness and case isolation can substantially decrease the transmission of SARS-CoV-2 in the population. Digital screening applications can prevent a substantial proportion of infections and may help to reduce the burden on healthcare systems.

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Supplementary Material

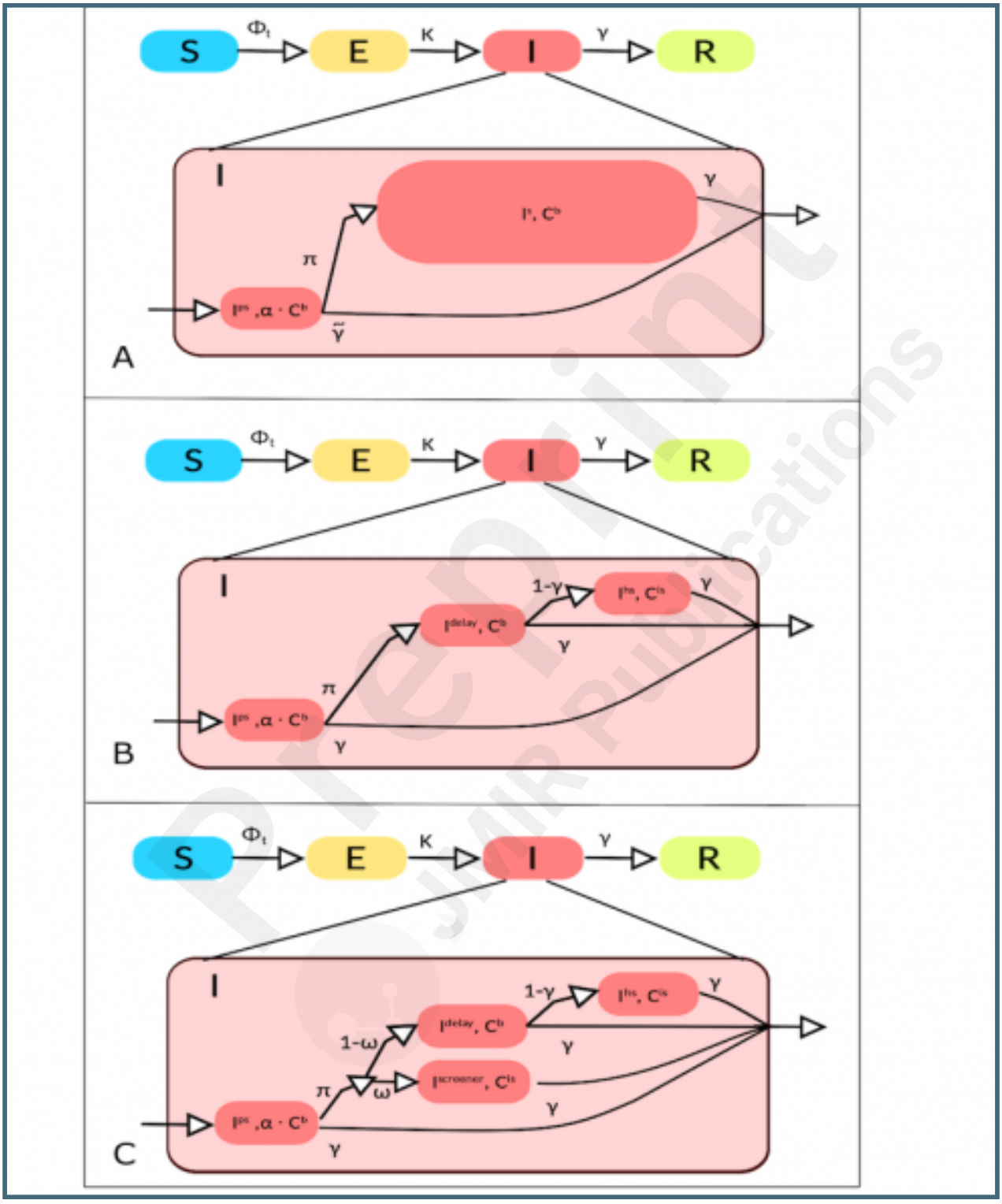
Supplementary Table 1: Population structure data (in thousand persons) for Germany, the UK, and the USA

Location	Germany	Germany	UK	UK	USA	USA
Year	2020	2020	2020	2020	2020	2020
Age Group	Female	Male	Female	Male	Female	Male
0-4	1 976	2 082	1 915	2 009	9 621	10 055
5-9	1 852	1 970	2 011	2 109	9 799	10 246
10-14	1 832	1 979	1 934	2 022	10 312	10 778
15-19	1 969	2 150	1 806	1 881	10 409	10 834
20-24	2 171	2 382	2 002	2 073	10 936	11 323
25-29	2 302	2 522	2 209	2 275	11 691	12 144
30-34	2 619	2 823	2 346	2 361	11 350	11 703
35-39	2 656	2 774	2 308	2 280	10 757	10 859
40-44	2 508	2 552	2 160	2 148	10 176	10 119
45-49	2 576	2 608	2 168	2 128	10 085	9 969
50-54	3 328	3 353	2 353	2 281	10 258	10 320
55-59	3 414	3 393	2 307	2 232	10 840	10 702
60-64	2 966	2 855	1 985	1 920	10 619	10 050
65-69	2 532	2 291	1 734	1 647	9 354	8 465
70-74	2 043	1 791	1 764	1 625	7 709	6 646
75-79	2 006	1 632	1 305	1 137	5 401	4 327
80-84	1 900	1 359	970	767	3 656	2 806
85-89	1 022	613	639	439	2 372	1 539
90-94	522	237	321	170	1 348	703
95-99	159	46	96	35	448	179
100+	16	4	13	3	76	21

Supplementary Files

Figures

Structure of the SEIR model, with A) the base case of no interventions and pre-symptomatic transmission, B) self-isolation of symptomatic cases with delay, and C) immediate self-isolation of symptomatic cases when using a digital screening application or delayed self-isolation otherwise.



Daily infectious (left) and total cumulative number of infected cases (right) for Germany (top), the UK (middle) and the USA (bottom) for different modelling scenarios. The dashed line indicates the introduction of NPI 60 days after the introduction of SARS-CoV-2 to the population.