Epidemics 42 (2023) 100658

Contents lists available at ScienceDirect

Epidemics

journal homepage: www.elsevier.com/locate/epidemics

Testing a simple and frugal model of health protective behaviour in epidemic times

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ARTICLE INFO

Keywords:
COVID-19
Health protective behaviour
Agent-based model
Calibration
Pattern-oriented modelling

ABSTRACT

The COVID-19 epidemic highlighted the necessity to integrate dynamic human behaviour change into infectious disease transmission models. The adoption of health protective behaviour, such as handwashing or staying at home, depends on both epidemiological and personal variables. However, only a few models have been proposed in the recent literature to account for behavioural change in response to the health threat over time. This study aims to estimate the relevance of TELL ME, a simple and frugal agent-based model developed following the 2009 H1N1 outbreak to explain individual engagement in health protective behaviours in epidemic times and how communication can influence this. Basically, TELL ME includes a behavioural rule to simulate individual decisions to adopt health protective behaviours. To test this rule, we used behavioural data from a series of 12 cross-sectional surveys in France over a 6-month period (May to November 2020). Samples were representative of the French population (N = 24,003). We found the TELL ME behavioural rule to be associated with a moderate to high error rate in representing the adoption of behaviours, indicating that parameter values are not constant over time and that other key variables influence individual decisions. These results highlight the crucial need for longitudinal behavioural data to better calibrate epidemiological models accounting for public responses to infectious disease threats.

1. Introduction

The COVID-19 pandemic has shed light on the need for public health authorities to have reliable simulation tools in order to prevent or control the spread of infectious diseases (Keeling et al., 2021; Mari et al., 2021; Gatto et al., 2020). Typically, epidemiologists have long applied a compartmental approach to predict the dynamic nature of an epidemic, such as SIR models. However, these epidemiological models, often based on ordinary differential equations used to describe how the disease is spreading, rarely incorporate a dynamic behavioural component of decision making under risk to explain how people deal with the evolving parameters of an epidemic (Funk et al., 2015; Ferguson, 2007; Diekmann and Heesterbeek, 2000). Therefore, individuals' decisions to adopt protective behaviours to prevent infection are often either exogenous or simply ignored. Despite the critical role that human behaviour, through person-to-person contacts, plays in increasing or reducing respiratory infectious disease transmission, risk of infection has to date mostly been examined through the lens of population density and mobility, which overlooks the dynamics of social and health behaviours.

In the current literature, epidemiologists are increasingly interested in the modelling of human behaviour and its influence on the spread of an epidemic (Verelst et al., 2016; Manfredi and d'Onofrio, 2013; d'Onofrio and Manfredi, 2009). One possible way of modelling is to represent health protective behaviours in ordinary differential equations based models (Buonomo and Della Marca, 2020). However, this approach is not satisfactory because it does not adequately represent sophisticated behavioural decision rules. Whereas this type of modelling considering human behaviour as exogenous can lead to an overall good prediction, it often results in an inaccurate prediction at the individual level. It is only suitable if the modeller aims to predict the spread of the epidemic. If he wants to study the effect of non-pharmaceutical interventions on this one, modelling the dynamics of human behaviour is unavoidable (Bedson et al., 2021; Funk et al., 2010). In particular, he needs to take account of the interactions between individuals and those

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https://doi.org/10.1016/j.epidem.2022.100658
Received 29 January 2022; Received in revised form 9 July 2022; Accepted 1 September 2022
Available online 5 December 2022

between people and their environment. In this respect, agent-based modelling is a promising method. This computational approach is increasingly used to describe infectious disease transmission (Weston et al., 2018; Verelst et al., 2016) because it is powerful to study the effects of changes in health protective behaviours on the spread of an epidemic. A few agent-based models have been developed to take account of the dynamics of human behaviour in disease transmission (Mniszewski and Del Valle, 2013), some of which a smaller number focused on COVID-19 (Lorig et al., 2021; Lu et al., 2021).

In light of the COVID-19 pandemic and of the potential risk of even worse future pandemics, it seems crucial to estimate the relevance and interest of existing agent-based models of health protective behaviours, for which the decision to adopt protective behaviours depends on a small number of social cognitive variables. This is the objective of this article. Specifically, we focus on what, in our opinion, may represent one of the most promising agent-based models, the TELL ME model introduced by Badham and Gilbert (2015), as it offers a relatively simple and frugal tool to represent change in health protective behaviours over time.

1.1. The agent-based modelling of human behaviours

Only a small number of disease transmission models provide an explicit modelling of individual behaviour during an epidemic. In their systematic review of behavioural change models applied to infectious disease transmission, Verelst et al. (2016) observe five types of modelling to represent the individual decision-making process. The behavioural decision can be exogenous, based on an information threshold, depend on information modelled as a dynamic parameter, or be based on an economic objective function with or without social learning or imitation. The TELL ME model belongs to this last category, rendering the decision to adopt protective behaviours dependent upon an objective function based on social cognitive factors, which includes subjective norms.

A challenge with which infectious disease modellers are faced is that their models are useful only insofar as they are able to identify how the agents react in an epidemic context and how they respond to prevention and control measures. This corresponds to the purpose of agent-based models of health protective behaviours (Funk et al., 2015). This modelling approach enables the simulation of individuals making decisions according to programmable rules (Badham et al., 2018). Contrary to traditional modelling methods, agent-based modelling focuses on individual interactions rather than individuals. Programmed rules define the interactions between agents and the interactions of agents with their environment. The model is run during a simulated time, in which agents make their decisions and adapt them. This method is thus useful to generate heterogeneity across population characteristics and to observe large-scale patterns (Bedson et al., 2021).

In their systematic review, Lorig et al. (2021) draw our attention to the rather striking heterogeneity among agent-based models in terms of purpose, transmission dynamics, geographical region and the number of simulated individuals. Only 14 % of the 126 agent-based social simulations included in the review implement agent behaviour by a fixed behavioural pattern based on an empirical schedule derived from personal characteristics. Further, 5 % of the simulations use dynamic or adaptive behavioural patterns, i.e. behaviour is based on needs or utility. Regarding simulation, only 43.7 % use real-world census data to take into account sociodemographic features and to generate a population similar to the population in the simulated region or country. Furthermore, the simulation methods in agent-based modelling are based on the confrontation of data to multiple criteria to evaluate the best parameter set. Nonetheless, in the existing models, the choice of the best parameter set is made by using an arbitrary acceptance threshold, as categorical calibration, or arbitrarily by prioritising one criterion over the others. A rigorous selection method is rarely used.

1.2. The TELL ME model of health protective behaviours

In this paper, we investigate the relevance of an adaptive behavioural pattern. This pattern is based on the three most cited psychological theories of health behaviour in disease transmission models and emergency response studies (Weston et al., 2020): i) the health belief model (Rosenstock, 1974); ii) the theory of planned behaviour (Ajzen, 1991); and iii) the protection motivation theory (Maddux and Rogers, 1983). The TELL ME model is one of the rare agent-based models to integrate the main components of these three main psychological theories into a model of behavioural change. More precisely, this agent-based model, constructed by Badham and Gilbert (2015), follows two pillars: i) an epidemiological model which simulates the spread of an epidemic, and ii) a behavioural rule which represents individual decision-making about protective behaviour.[1] This model, which was developed in the framework of the TELL ME European Project on transparent communication during epidemics, aims to simulate the effect of different communication strategies on the individual protective decisions in an epidemic context (Barbrook-Johnson et al., 2017).[2]

The TELL ME behavioural rule bases the decision to adopt protective behaviours on attitude, subjective norms and perceived threat associated with the epidemic. The relevance of this design has been confirmed by empirical data. Reviewing studies of epidemics from 2002 to 2010, Bish and Michie (2010) found strong evidence that perceived susceptibility, perceived disease severity, and perceived efficacy of behaviour are significantly associated with engaging in protection against the disease. There is also a limited amount of evidence in favour of social norms as a predictor of protective behaviours. In a recent integrated narrative review based on the period from 2000 to 2020, Seale et al. (2020) found that isolation was influenced by perceived susceptibility and perceived efficacy. During the COVID-19 epidemic, some studies examined the association of sociodemographic, cognitive and psychological variables with the adoption of health protective behaviours. Once again, engaging in health protective behaviours, such as mask wearing and social distancing, is found to be strongly associated with perceived efficacy (Scholz and Freund, 2021; Clark et al., 2020; Zickfeld et al., 2020). Moreover, perceived infection risk is also revealed to be a significant predictor of behaviours (Qin et al., 2021; Schneider et al., 2021; Bruine de Bruin and Bennett, 2020; Ning et al., 2020; Storopoli et al., 2020; Vally, 2020). In France, two studies investigated these relationships during the first lockdown. Raude et al. (2020) highlighted the role of perceived efficacy, perceived severity and subjective norms in the adoption of protective behaviours. For their part, Guillon and Kergall (2020) found that perceived threat and perceived benefits influence attitudes and opinions regarding quarantine.

Based on psychological theories, TELL ME is one of the rare agent-based models to simulate the spread of an epidemic by incorporating personal and epidemiologic variables. The objective of our study is to investigate the validity of the TELL ME behavioural rule to explain engagement in protective behaviours during the COVID-19 pandemic. In particular, we look at to what extent this rule is able to represent the overall behaviour of the population and individual behaviours. Further, we study whether the variables included in this rule are the most relevant and which variables should be endogenised, as well as what minimal level of detail is required to capture individual differences in protective behaviour.

[1] See TELL ME (2015) for details on prototype software.

[2] A description of the TELL ME European project is available online: https://www.tellmeproject.eu/ Accessed July 8, 2022.

2. Materials and methods

2.1. Variables of the TELL ME model

As indicated previously, the TELL ME model focuses on the behavioural rule which is based on three leading theories in health psychology: i) the theory of planned behaviour; ii) the health belief model; and iii) the protection motivation theory. For an agent, it is assumed that the decision to adopt protective behaviour depends on three key variables drawn from these theories: attitude toward the behaviour, subjective norms and perceived threat.

In the following, we summarise the main concepts regarding these constructs and how we implemented them in the present study:

Attitude: This construct is generally defined as beliefs about the behaviour and its consequences, which underlie the willingness to adopt protective behaviour. Initially, Badham and Gilbert applied their model to the self-protective behaviours occurring during the 2009 H1N1 epidemic, for which they used an empirically-based distribution extracted from the responses to questions about hand hygiene throughout the epidemic, as reported in Cowling et al. (2010). In line with the psychological theories of health behaviours (Brewer and Rimer, 2008; Weinstein, 1993), in our analysis we disaggregated attitude into two associated variables: perceived efficacy and perceived barriers regarding protective behaviours. The first variable captures the *expected benefit* of the adoption of the protective behaviour by the agent, whereas the second assesses the *expected cost* of that behaviour. In our study, perceived efficacy and perceived barriers of protective behaviours were based on multi-item scale variables. These scores, between 0 and 1, represent averages of the responses to the following questions: i) for perceived efficacy (items from 0 to 10), "How effective do you think the improved hygiene measures are to prevent the COVID-19 infection?", and "How effective do you think the social distancing measures are to prevent the COVID-19 infection?"; and ii) for perceived barriers (items from 0 to 10, in the reverse order for the analysis), "How difficult do you think it is to adopt improved hygiene measures to prevent COVID-19 infection?", and "How difficult do you think it is to adopt social distancing measures to prevent COVID-19 infection?".

Subjective norms: This construct refers in the literature to the "beliefs about the normative expectations of others" which lead to perceived social pressure (Stroebe, 2011). They are captured in the model through the proportion of agents in the same region that have adopted the behaviour. The underlying assumption is that agents make their decisions according to the behaviour expected by their family, friends and other people who are important to them, and how they perceive this behaviour as a benchmark. In our study, subjective norms were measured through the proportion of agents' in the same administrative region having adopted the behaviour, i.e. the proportion of "high compliance" response in each region.

Perceived threat: This construct is often defined as the product of two components (Brewer et al., 2007): the perceived severity and frequency of the disease. Based on Durham and Casman's method (2012), Badham and Gilbert (2015) represent the frequency of the disease as a cumulative incidence time series, i.e. the sum of the current incidence level and the discounted past incidence levels. In our study, we made two important modifications to this model. Firstly, we used the death incidence, defined by the number of new deaths per day, instead of the number of infected persons as the latter variable is not reliable due to underdetection of symptomatic COVID-19 cases (Pullano et al., 2021; Shaman, 2021). Secondly, we computed incidence at the national rather than the regional level. Indeed, during the epidemic, people were massively informed about the daily number of deaths in the country through intensive media coverage, whereas knowing the number of deaths in their region required an additional effort in the form of an information search. In our study, incidence was measured by the publicised number of deaths expressed in thousands. For each period, cumulative incidence time series comprises the current death incidence level and the death incidence in the last three weeks. The severity component refers to the perceived consequences of becoming infected. We performed an ANOVA to explore the difference in perceived severity over time. The difference was associated with a small effect (η^2=0.01). That is why we assumed in our analysis that the perceived severity of infection is stable over time and we set the severity multiplier to 1, as Badham and Gilbert did for this factor in their initial study.

Health protective behaviours: In our analysis, we sought to explain the change in the adoption of a range of protective behaviours recommended by the authorities to tackle the COVID-19 epidemic. More precisely, we analysed six protective behaviours, including: 1) "Avoid close contacts with other people"; 2) "Avoid public transport"; 3) "Do not shake hands"; 4) "Stay at least 1 m away from other people"; 5) "Stay home as much as possible"; and 6) "Wash hands often". In each of our surveys, participants were asked whether they engaged in each of these behaviours to reduce their risk of infection from COVID-19. They had to answer "Yes, systematically", "Yes, often", "Yes, sometimes", or "No, never". As we observed a ceiling effect in the responses in favour of the upper limit of the scale, we dichotomized each behaviour variable with the "high compliance" response ("Yes, systematically") coded as 1, and the other options merged into a "lower compliance" category coded as 0. Percentages of people who reported engaging in protective behaviours over time are displayed in Fig. 1.

For each protective behaviour, Table 1 indicates the difference in means of each component of the behaviour score between the agents who adopted the protective behaviour and the agents who did not. We see that all differences are significant, except for subjective norms, when the prescribed protective behaviour is "Wash hands often", which can be explained by a small variance in this behaviour over time. Overall, our data show that all variables are significantly associated with the decision to adopt behaviour. Therefore, their inclusion in the TELL ME agent-based model is appropriate.

2.2. Behavioural decision rule

The TELL ME behavioural decision rule can be described as follows. An agent i that at time t is in the region r adopts the protective behaviour if his behaviour score (B_i) at the time t is greater than or equal to a threshold score (T). In the converse case, the behaviour is dropped. The behaviour score (B_i) is a weighted average of perceived efficacy (E_i), perceived barriers (C_i), subjective norms (N_r) and incidence (INC):

$$B_i(t) = \alpha E_i(t) + \beta C_i(t) + \gamma N_r(t) + (1 - \alpha - \beta - \gamma) W \sum_{j=0}^{t} \delta^j INC(t - j)$$

where α, β, γ are weights, δ is a discount rate and $W = 1$. The scores of perceived efficacy and perceived barriers are personal characteristics. Subjective norms are identical to all agents in the region r and, of course, cumulative incidence time series expressed in thousands is the same for all agents.

2.3. Samples and data

Our data was collected through 12 online, cross-sectional surveys conducted from May to November 2020 among large representative samples of adults residing in France.[3] Therefore, the period studied does not cover the strict French lockdown which was implemented from 17 March to 10 May. Only the last two surveys took place during a less strict lockdown, in which schools were open and face-to-face work was possible. A stratified sampling method was adopted to recruit participants so as to represent the distribution of the French population, based on sex, age, occupation, community size and region recorded during the

[3] Surveys were conducted by the BVA research institute (https://www.bvagroup.com/en/about-us/).

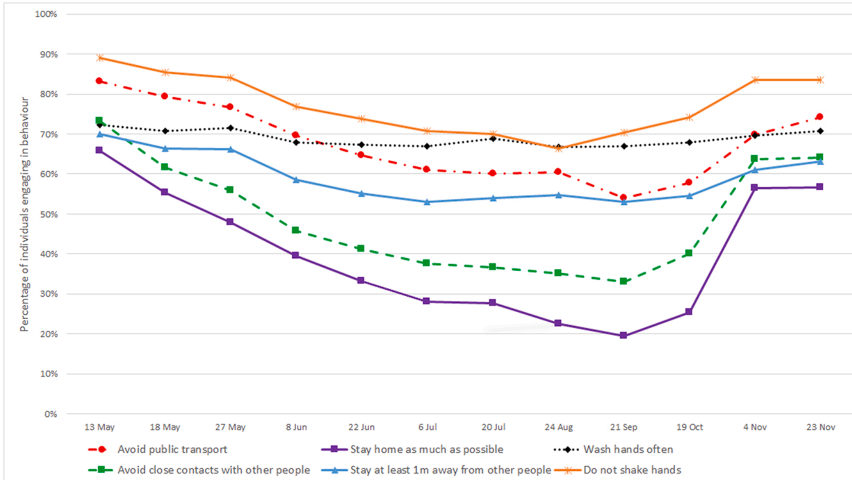

Fig. 1. Percentages of participants engaging in protective behaviours over time in 2020. For each survey, each curve indicates the percentage of respondents who reported engaging in the particular protective behaviour.

Table 1
Mean differences according to the adoption of the protective behaviour ($y = 1$ vs. $y = 0$).

	Protective behaviour					
Variables	Avoid close contacts with other people	Avoid public transport	Do not shake hands	Stay at least 1 m away from other people	Stay home as much as possible	Wash hands often
Efficacy	0.0491223 * **	0.0309255 * **	0.0799952 * **	0.0610779 * **	0.0310983 * **	0.0570135 * **
Barriers	0.0217058 * **	0.0328359 * **	0.0417856 * **	0.0357394 * **	0.0222339 * **	0.0394996 * **
Norms	0.0757643 * **	0.0538871 * **	0.0248763 * **	0.0146448 * **	0.1057802 * **	-0.0006659
Incidence (day)	0.0645354 * **	0.0316636 * **	0.0430373 * **	0.0194769 * **	0.0743378 * **	0.00808 * **
Incidence (a week ago)	0.0657756 * **	0.0401469 * **	0.0460148 * **	0.0242512 * **	0.0765453 * **	0.0096581 * **
Incidence (two weeks ago)	0.0724176 * **	0.0509014 * **	0.0526307 * **	0.0303889 * **	0.0846327 * **	0.0113325 * **
Incidence (three weeks ago)	0.0845054 * **	0.0683834 * **	0.0649798 * **	0.040627 * **	0.099991 * **	0.0139123 * **

Note: Comparison of means by *t*-test. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

2016 national general census conducted by the National Institute of Statistics and Economic Studies (INSEE). Samples consisted of N = 24,003 responses. Missing data were replaced by a multivariate imputation procedure (van Buuren and Groothuis-Oudshoorn, 2011). More than half of these participants were women (56.87 %), and 14.18 % had a high socioeconomic status, 34.81 % had a low socioeconomic status, and another 51.01 % were inactive (retired, students and persons engaged in activities in the household). Ages were between 18 and 99 years, with a proportion of participants aged 65 years or older of 27.71 %. Ethical approval was granted by the University Hospital Institute “Mediterranee Infection” Ethics Committee Marseille, France and the EHESP School of Public Health Office for Personal Data Protection.

2.4. Calibration process

We are not interested in this paper in the epidemiological component of the TELL ME model. Indeed, our purpose is not simulating the spread of the COVID-19 epidemic. Rather, we aim to determine to what extent the TELL ME behavioural rule is powerful in explaining the individual decisions to adopt protective behaviours during the epidemic. Five parameters are involved in the behavioural rule: the weights for perceived efficacy, perceived barriers and subjective norms, the discount rate of past incidence levels, and the threshold score ($\alpha, \beta, \gamma, \delta, T$).

Our calibration process was based on the method used by Badham et al. (2017) in their own estimation of the TELL ME model. Their originality is to estimate their model against multiple macro validation criteria, that is pattern-oriented modelling (Railsback and Grimm, 2012; Wiegand et al., 2004). This simulation method is particularly useful to obtain both an overall good fit and an individual good fit. Indeed, with a sufficient number of parameters, an accurate assessment of percentages of individuals engaging in protective behaviours can be easily achieved, but such a fit may be associated with a problem of structural invalidity or other problems. For instance, the model can report the correct percentage of people adopting the behaviour in the targeted population, but it wrongly predicts that a careful agent does not adopt behaviours, or that a careless agent adopts behaviours.

Having multiple selection criteria raises the question of how to choose the best fit parameter set. This may be chosen on the basis of an overall objective function in which each criterion would be weighted, the reasonableness of the model’s behaviour or an acceptance threshold for each criterion. The problem is that the choice of priority criterion or acceptance threshold is arbitrary and sometimes inefficient. That is why Badham et al. use a dominance analysis, which is already used in operations research for multi-criteria decision-making or optimisation (Müssel et al., 2012). Although this approach is scarce in social simulation, it is powerful in improving the fit with the empirical behaviour adoption curve. Dominance analysis involves determining all best fit candidates on the Pareto efficient frontier. On this frontier, an improvement in one criterion inevitably requires a reduction in another.

Although it required some adjustments, in particular due to the absence of an epidemiological component in our analysis, the simulation method of Badham et al. was easy to implement with our data and consisted of four steps. The first challenge was to generate enough heterogeneity in the agents' behaviour. To do this, as indicated in Table 2, we excluded parameter combinations for which the behaviour score was not computed from perceived efficacy, perceived barriers, subjective norms and perceived threat ($\alpha + \beta + \gamma \leq 0.95$). Moreover, the range of the discount rate was restricted ($\delta \leq 0.44$) to prevent cumulative incidence time series to exceed 1. We sampled the parameter space by the Latin Hypercube method and selected 3587 combinations, i.e. 1 % of all possible combinations.

Second, we assessed the behavioural adoption curve associated with each combination against empirical data on two criteria: 1) the mean squared error between predicted and actual behaviour (MSE); and 2) the maximum difference in absolute terms between the predicted adoption proportion and actual adoption proportion per period (ΔMax). Indeed, MSE is an insufficient criterion to capture the shape of the behavioural adoption curve. Integrating the criterion ΔMax in the analysis permits us to take the shape into account. Contrary to Badham et al., we did not use a third criterion that would be the number of days between the timing of the maximum predicted adoption proportion and the maximum actual adoption proportion. This criterion is applicable only in the case where the agent-based model is launched. Our interest here is only to estimate the validity of the behavioural rule without looking at the epidemiological model.

Third, dominance analysis was used to identify the best fit candidates. The principle is to assign each parameter set to a dominant front. Front 0 corresponds to the Pareto efficient frontier. Front 1 would be the Pareto efficient frontier if we remove front 0 parameter sets. We proceeded in the same way for higher front values until all parameter sets were assigned.

Finally, to determine the best fit parameter set, we needed to distinguish between Pareto efficient sets. To this end, we selected the combination that minimised the average of MSE and ΔMax, i.e. individual and total estimation errors. Thus, the selected parameter set places the estimated behaviour curve close to the empirical one, while ensuring a small individual estimation error. Simulation and dominance analyses were performed with Matlab.

3. Results

3.1. Selection of the best fit parameter set

The parameter sets on the Pareto efficient frontier are not dominated. On this frontier (front 0), it is not possible to distinguish between parameter sets on the basis of the two criteria MSE and ΔMax. An improvement in one criterion implies a reduction in the other one. For each protective behaviour, Fig. 2 displays the fit for all parameter sets. The best fit candidates on the Pareto efficient frontier are in bold and black. We see that the number of candidates depends on protective behaviour. For example, "Wash hands often" is associated with 61 best fit candidates, whereas there are only 11 for "Stay at least 1 m away from other people". Regarding both selection criteria, on the one hand, the MSE associated with these parameter sets is never lower than 0.2247 (achieved for "Do not shake hands"). MSE indicates the mean squared difference between the observed value and the estimated one. In our analysis, as the dependent variable is binary, MSE also represents the percentage of errors in individual predictions of engagement in protective behaviours. In other words, MSE is a measure of individual accuracy of the behavioural rule. Thus, we can argue that this is not possible to reduce the percentage of error in estimating the agent's protective behaviour below 22.47 %. On the other hand, the Pareto efficient frontier exhibits parameter sets for which ΔMax is small (e.g. 0.0485 for "Avoid close contacts with other people"). ΔMax can be considered as a measure of overall accuracy. On this point, our simulation reveals that the TELL ME behavioural rule estimates quite accurately the total percentage of individuals engaging in protective behaviours. Our two accuracy measures lead us to conclude that while individual estimation error remains moderate to high, total estimation error can be very low. This means that although some decisions of engagement in protective behaviours are mispredicted, the predicted adoption proportion by period is not far from the observed one. Overall, the prediction of the percentages of individuals engaging in protective behaviours at a population level is good but the individual prediction is inaccurate.

Table 2
Parameter values tested in the calibration process.

Parameter	Range
Efficacy weight (α)	0.05 by 0.05–0.85
Barriers weight (β)	0.05 by 0.05–0.85
Norms weight (γ)	0.05 by 0.05–0.85
Incidence discount (δ)	0.02 by 0.02–0.44
Behaviour threshold (T)	0.05 by 0.05–0.95

The Pareto approach highlights a trade-off between individual estimation error and the total one. To select the best fit parameter set among candidates on the Pareto efficient frontier, we minimised the average of both error types. This method led us to choose the parameter sets reported in Table 3. For each protective behaviour, the total estimation error is small, while individual estimation error remains moderate at best, i.e. the percentage of individuals engaging in protective behaviour is consistent but there are many individual estimation errors. Individual estimation error is the lowest for the behaviour "Do not shake hands" (28.52 %) and the highest for the behaviour "Avoid close contacts with other people" (41.89 %).

For a better visualisation of fit quality, actual and estimated percentages of individuals engaging in protective behaviours by survey are represented in Fig. 3 and percentages of errors in individual predictions by survey are displayed in Fig. 4. As expected, we see in Fig. 3 that our method implies close behaviour curves. Moreover, except for some periods, the slopes of behaviour curves are of the same sign. Fig. 4 shows that individual estimation error varies over time for all behaviours and, in particular, for both "Avoid public transport" and "Do not shake hands". Notably, it is at least 18.25 % for the behaviour "Do not shake hands" on 13 May and at most 47.55 % for the behaviour "Avoid public transport" on 21 September.

3.2. Analysis of the parameter set

Although MSE is never small, the analysis of parameter values is interesting to understand how people make their decisions to adopt protective behaviours and how to provide them with good incentives. The six behaviours are characterised only by four different best fit parameter sets. Indeed, on the one hand "Avoid close contacts with other people" and "Stay home as much as possible", and on the other hand, "Avoid public transport" and "Wash hands often" share the same parameter sets. This indicates that people use the same decision rule for these protective behaviours.

We can analyse the importance of each parameter in the individual behaviour decisions. If each parameter behaves in the same way in the behaviour score, it should be equal to 0.25. If a parameter is more important, its weight should be greater than 0.25. In the opposite case, its weight should be lower than 0.25. With this method, we observe that all protective behaviours are associated with a high weight of perceived efficacy, which represents half of the behaviour score in each case ($\alpha \geq 0.5$). On the contrary, perceived barriers ($\beta \leq 0.25$) and perceived threat ($1 - \alpha - \beta - \gamma \leq 0.25$) are never determining factors in the behaviour score. Subjective norms are important only for "Avoid public transport" and "Wash hands often" ($\gamma = 0.3$). These distinctions suggest that the adoption of protective behaviours is mainly based on perceived efficacy, i.e. how improved hygiene measures and social distancing are perceived as effective in preventing COVID-19 infection. With discount rate as a proxy for time preference, we find that past incidence levels are

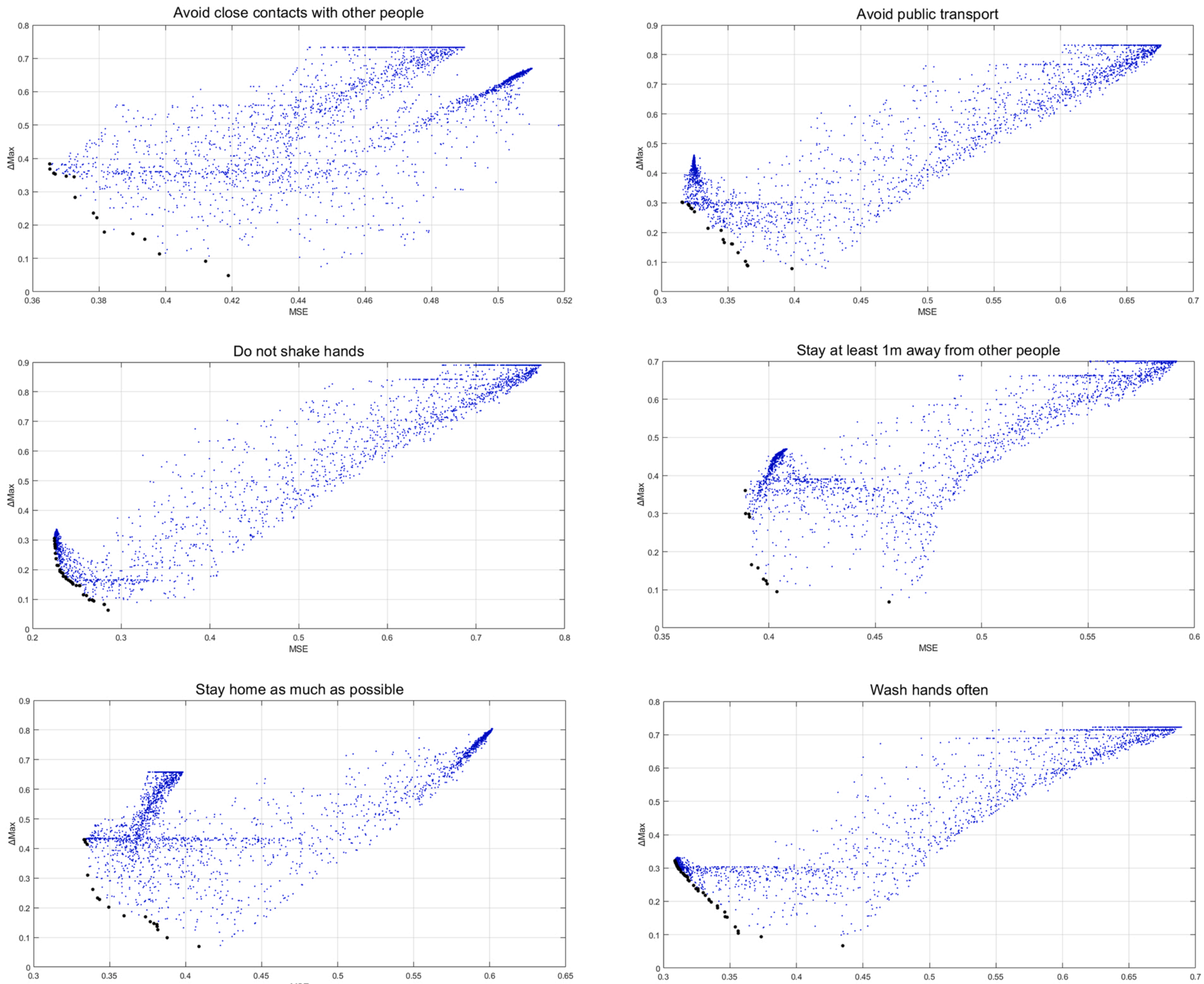

Fig. 2. Selection criteria for each of 3587 parameter sets by protective behaviour. Each graph corresponds to a different protective behaviour. In each graph, the values of both selection criteria MSE and *ΔMax* associated with each parameter set are represented. Parameter sets on the Pareto efficient frontier are in bold and black.

Table 3
Best fit parameter set by protective behaviour and their assessment.

	Parameter values						Criteria	
Protective behaviour	α	β	γ	$1-\alpha-\beta-\gamma$	δ	T	*MSE*	*ΔMax*
Avoid close contacts with other people	0.5	0.25	0.2	0.05	0.28	0.6	0.4189	0.0485
Avoid public transport	0.5	0.15	0.3	0.05	0.08	0.6	0.3649	0.0874
Do not shake hands	0.55	0.1	0.25	0.1	0.2	0.6	0.2852	0.063
Stay at least 1 m away from other people	0.75	0.05	0.1	0.1	0.24	0.65	0.4038	0.095
Stay home as much as possible	0.5	0.25	0.2	0.05	0.28	0.6	0.4088	0.0695
Wash hands often	0.5	0.15	0.3	0.05	0.08	0.6	0.3563	0.1045

practically ignored for two behaviours: “Avoid public transport” and “Wash hands often” ($\delta = 0.08$). For these last two protective behaviours, the perceived threat taken into account in the decision rule is almost reduced to the current incidence level.

4. Discussion

As part of the TELL ME European project, the TELL ME agent-based model was initially designed by Badham and Gilbert (2015) to model, based on leading health psychology theories, the effect of communication plans on protective behaviours during an epidemic. In their primary model, only three variables were included to explain the adoption of protective behaviours over time: attitude toward the behaviour, subjective norms, and perceived threat associated with the risk of infection. In line with the psychological theories underlying the TELL ME model, the construct of attitude was replaced in our analysis by two variables underlying behavioural change: perceived efficacy, and perceived barriers related to the protective behaviours. After the calibration process of the behavioural decision rule, we found the best fit parameter values associated with these variables. Simulation led to a good prediction of each percentage of individuals engaging in protective behaviour at a population level but the individual prediction is unsatisfactory. Indeed, for each protective behaviour, the percentage of error in estimation remains relatively high.

This high error could be due to a failure in the calibration process. In this paper, after considering all possible parameter values, we sampled

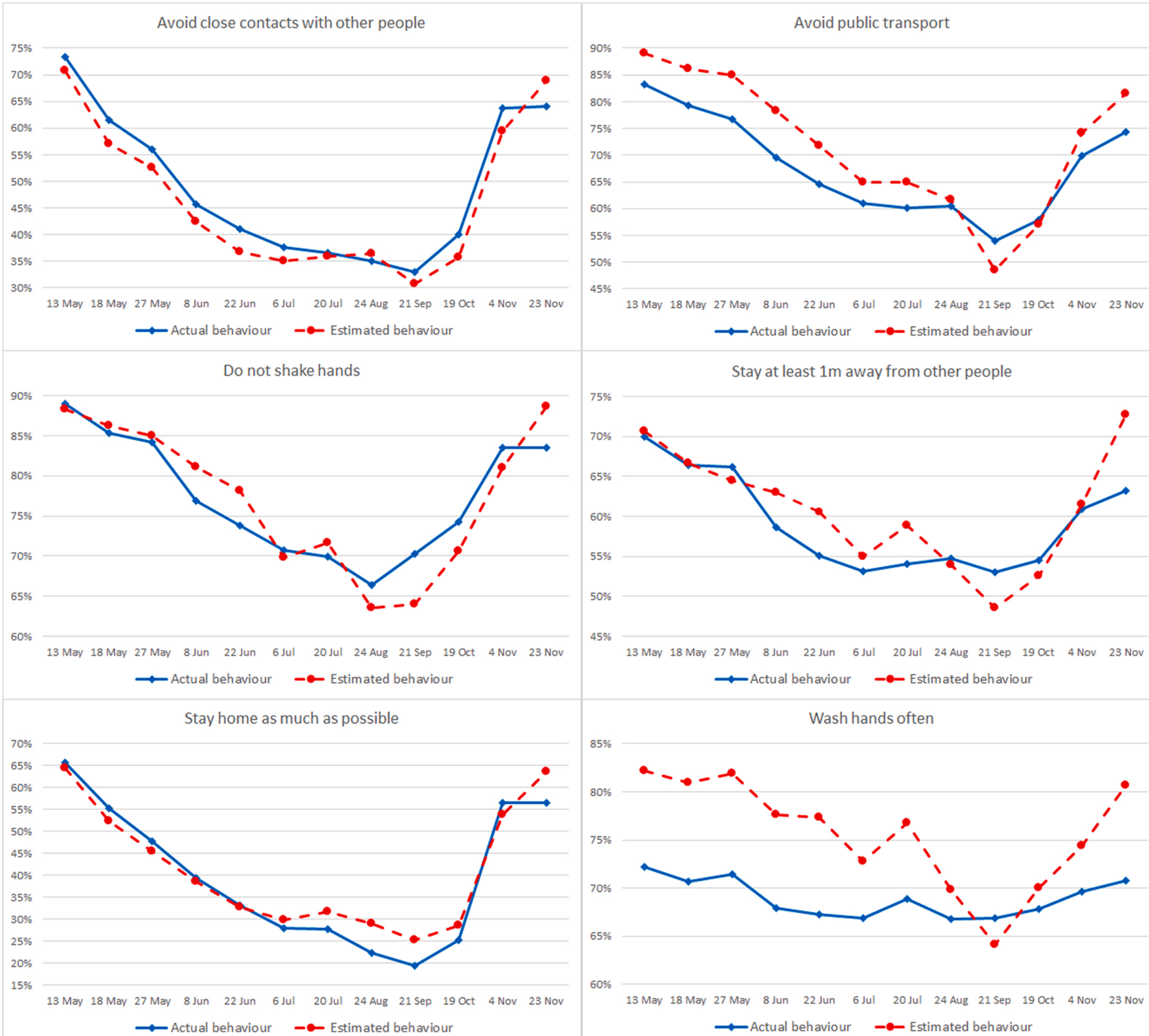

Fig. 3. Actual and estimated percentages of individuals engaging in protective behaviours over time. Each graph corresponds to a different protective behaviour. In each graph, for each survey, the blue continuous curve indicates the percentage of respondents engaging in protective behaviour. The red dash curve indicates the percentage of individuals engaging in protective behaviour as estimated by the TELL ME behavioural rule.

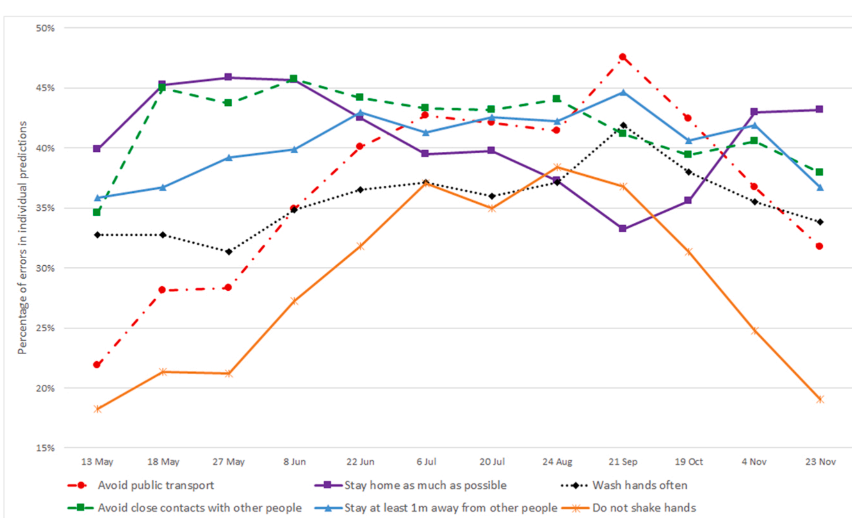

Fig. 4. Percentages of errors in individual predictions over time. For each survey, each curve indicates the percentage of errors in individual predictions of engagement in the particular protective behaviour.

the parameter space by the Latin Hypercube method to keep only heterogeneous parameter sets. Then, we selected the best fit parameter set on the basis of two criteria, the mean squared error between predicted and actual behaviour, and the maximum difference in absolute terms of the predicted adoption proportion and actual adoption proportion per period. A trade-off between these two criteria consisted of selecting the parameter set for which the average between the two error criteria was the smallest. This method is consistent with finding an estimated behaviour curve close to the observed one. However, this curve is associated with a high MSE. As shown in Fig. 2, even if we selected the parameter set with the minimum MSE, MSE would nonetheless remain high. Thus, it is clear that failure in calibration does not explain this error.

In contrast, the nature of our data can explain the error in individual predictions. Our analysis is based on 12 cross-sectional surveys. Compared to longitudinal data, cross-sectional investigations prevent us from studying how the behaviour of the same agent evolves over time. However, as revealed in Fig. 1, protective behaviours, and specifically social distancing measures, are not stable over time. Indeed, in our analysis, we succeeded in capturing the preferences of many agents in different time periods. To better control an epidemic, it is important for an estimation to reveal how the preferences of agents change depending on the evolution of the parameters of the epidemic. Unfortunately, for many reasons, only a few published studies of the COVID-19 epidemic use longitudinal data (Qin et al., 2021; Machida et al., 2020; Wise et al., 2020). Moreover, these studies generally cover a short period corresponding to the first wave of the epidemic. Therefore, they capture change in individual preferences during a timeline which does not represent all epidemic stages. To estimate the effect of public policies on individual protective behaviours, surveys should ideally be repeated with the same agents from the beginning of the epidemic to its end, or at least over several waves of the epidemic.

The high percentage of individual errors could also be the result of the design of the TELL ME behavioural rule. Predicting how individuals engage in protective behaviours in social simulations is mostly associated with high error. Indeed, point prediction with a simple rule in complex social systems cannot be inherently accurate (Polhill et al., 2021; Hofman et al., 2017). In our case, predictive power is limited by the individual heterogeneity that our frugal rule does not capture. The TELL ME behavioural rule including epidemiological and personal variables results in a MSE higher than 0.4 for three of the six protective behaviours, whereas a random decision rule would predict on average the right individual behaviour with a 50/50 chance, i.e. a MSE equal to 0.5. That is why the TELL ME behavioural rule cannot be used to predict individual protective behaviours and should be refined. Its simulation provides insights to understand better how to model the decision of engagement in protective behaviours.

We can identify two sources to improve the modelling of individual decisions to be protected. Firstly, in the computation of the behaviour score, the weights of perceived efficacy, perceived barriers, perceived threat, and the discount rate are common for all agents over time. Moreover, all agents in the same region have the same weight of subjective norms, regardless of the period. Nevertheless, the lack of individualisation among parameters does not allow us to capture the heterogeneity between agents, leading to an error in prediction. In practice, the effect of variables can also decline over time. For instance, it is more likely that agents adopt mimetic behaviours due to higher perceived social pressure at the beginning of an outbreak, i.e. the effect of subjective norms would be higher in the first periods than in the later ones. Besides, the number of daily deaths is probably not taken into account in the same way over time due to the phenomenon of behavioural fatigue (Petherick et al., 2021; World Health Organization, 2020) or a change in the perception of severity of the disease.

Secondly, our analysis tested a simple and frugal model, which includes only four epidemiological and personal variables. As referenced in the systematic review report of the TELL ME European project from studies on SARS and H1N1 epidemics (TELL ME, 2012), other variables might be involved in the decision to adopt protective behaviours. Among sociodemographic factors, recent empirical studies of the COVID-19 epidemic highlighted that being a woman, elderly or having a high level of formal education is associated with a higher probability of engaging in the various protective behaviours (Papageorge et al., 2021; Smith et al., 2021; Wright and Fancourt, 2021; Lüdecke and von dem Knesebeck, 2020). Similarly, other potential cognitive and cultural variables seem to determine the adoption of such behaviours. It is highly plausible that anxiety and emotional distress, perceived self-efficacy, trust in science and institutions, or ideological world views may be predictors of engagement in protective behaviours (Schneider et al., 2021; Scholz and Freund, 2021; Qin et al., 2021; Clark et al., 2020; Ning et al., 2020; Storopoli et al., 2020; Ye and Lyu, 2020). Obviously, neglecting these determinants of behavioural decision-making generates a large gap between empirical data and predicted values.

Finally, by showing that a simple behavioural rule cannot result in an accurate prediction of the individual decision to be protected, our study also allows us to discuss the external validity of the results of epidemiological models. In particular, caution is advised towards extrapolating the results of compartmental models. As these models exclude personal variables, it is likely that their predictive power is even poorer than the TELL ME behavioural rule. Compartmental models may be efficient to predict the spread of an epidemic, but it is doubtful that they are suitable to predict individual behaviours. Instead, in order to make individual predictions, epidemiologists should rely on models in which the decision to engage in protective behaviours is represented by a rule based on recent psychological findings and on modelling sufficient individual heterogeneity.

5. Conclusion

The objective of this paper was to estimate the relevance of the behavioural decision rule proposed by the TELL ME agent-based model in the COVID-19 epidemic context. According to this rule, the decision to adopt protective behaviours depends on attitude, subjective norms and perceived threat associated with the COVID-19 epidemic. Overall, our simulation of this decision rule, using 12 cross-sectional surveys conducted in France from May to November 2020, highlights a relatively high error in prediction of individual behaviours. It appears therefore that the relevance of this rule to predict the decision to adopt protective behaviours cannot be taken for granted. Notwithstanding this persistent error in prediction, our analysis provides some insights to bridge the gap between theory and empirical data. In particular, there is a need for individualising the effects of epidemiological and personal variables, including other variables which are cognitive, psychological and sociodemographic, as well as for the collection of longitudinal data during a sufficiently long period. These issues should be integrated in future epidemiological simulations to enable public authorities ultimately to better control epidemic disease spread.

Funding

This work was supported by the European Union's Horizon 2020 research and innovation program "PERISCOPE: Pan European Response to the ImpactS of COvid-19 and future Pandemics and Epidemics", under the grant agreement No. 101016233, H2020-SC1-PHE_CORONAVIRUS-2020-2-RTD.

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& editing, **Jocelyn Raude:** Conceptualization, Data curation, Investigation, Writing - original draft, Writing - review & editing, Project administration, Supervision, Funding acquisition.

Declaration of Competing Interest

The authors declare no competing interests.

Acknowledgements

The authors are grateful to Dr Pierre Arwidson and the COVIPREV group from the Department of Health Promotion and Prevention (Santé Publique France) for their valuable support.

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