

1     **How have mathematical models contributed to understanding**  
2           **the transmission and control of SARS-CoV-2 in healthcare**  
3                   **settings? A systematic search and review**

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23 **Abstract**

24 **Background:** Since the onset of the COVID-19 pandemic, mathematical models have been  
25 widely used to inform public health recommendations regarding COVID-19 control in  
26 healthcare settings.

27 **Objectives:** To systematically review SARS-CoV-2 transmission models in healthcare  
28 settings, and summarise their contributions to understanding nosocomial COVID-19.

29 **Methods:** Systematic search and review.

30 **Data sources:** Published articles indexed in PubMed.

31 **Study eligibility criteria:** Modelling studies describing dynamic inter-individual transmission  
32 of SARS-CoV-2 in healthcare settings, published by mid-February 2022.

33 **Participants and interventions:** Any population and intervention described by included  
34 models.

35 **Assessment of risk of bias:** Not appropriate for modelling studies.

36 **Methods of data synthesis:** Structured narrative review.

37 **Results:** Models have mostly focused on acute care and long-term care facilities in high-  
38 income countries. Models have quantified outbreak risk across different types of individuals  
39 and facilities, showing great variation across settings and pandemic periods. Regarding  
40 surveillance, routine testing – rather than symptom-based testing – was highlighted as  
41 essential for COVID-19 prevention due to high rates of silent transmission. Surveillance  
42 impacts were found to depend critically on testing frequency, diagnostic sensitivity, and turn-  
43 around time. Healthcare re-organization was also found to have large epidemiological  
44 impacts: beyond obvious benefits of isolating cases and limiting inter-individual contact,  
45 more complex strategies such as staggered staff scheduling and immune-based cohorting  
46 reduced infection risk. Finally, vaccination impact, while highly effective for limiting COVID-  
47 19 burden, varied substantially depending on assumed mechanistic impacts on infection

48 acquisition, symptom onset and transmission. Studies were inconsistent regarding which  
49 individuals to prioritize for interventions, probably due to the high diversity of settings and  
50 populations investigated.

51 **Conclusions:** Modelling results form an extensive evidence base that may inform control  
52 strategies for future waves of SARS-CoV-2 and other viral respiratory pathogens. We  
53 propose new avenues for future models of healthcare-associated outbreaks, with the aim of  
54 enhancing their efficiency and contributions to decision-making.

55 **Introduction**

56 SARS-CoV-2 transmission in healthcare settings has contributed significantly to the global  
57 health-economic burden of COVID-19. Healthcare settings are particularly vulnerable to  
58 COVID-19, due to dense concentrations of frail patients, high frequencies of at-risk medical  
59 procedures, and high rates of inter-individual contact. Both patients and healthcare workers  
60 (HCWs) have been at high risk of SARS-CoV-2 infection throughout the pandemic, resulting  
61 in major nosocomial outbreaks worldwide [1,2]. In England, for instance, an estimated 20%  
62 of patients hospitalized with COVID-19 before August 2020 acquired their infection in  
63 hospital [3], while 95,000-167,000 patients became infected during their hospital stay  
64 between June 2020 and March 2021 [4]. Further, HCWs have experienced an estimated 1.6-  
65 to 3.4-fold higher risk of infection relative to the general population [5,6]. Long-term care  
66 facilities (LTCFs) have been most severely impacted, with one- to two-thirds of COVID-  
67 related deaths in Europe by May 2020 estimated to have occurred among LTCF residents  
68 [7].

69 Healthcare facilities have undergone extensive organizational changes to combat SARS-  
70 CoV-2 transmission, particularly during local surges in COVID-19 cases. Many facilities have  
71 adopted non-pharmaceutical infection prevention and control (IPC) measures, including  
72 social distancing, reinforced contact precautions and hand hygiene procedures, use of  
73 personal protective equipment (PPE), banning of visitors, and systematic test-trace-isolate  
74 protocols. HCWs and residents of LTCFs have also been among the first populations  
75 targeted for vaccination. However, despite these interventions, nosocomial COVID-19 risk  
76 has not been eliminated, as evidenced by ongoing outbreaks in healthcare facilities  
77 worldwide. A key barrier to effective COVID-19 prevention in healthcare settings is imperfect  
78 understanding of transmission routes among patients and HCWs, and of the relative impacts  
79 of different control strategies, which depend on setting-specific organizational and  
80 demographic characteristics, immunological histories of the specific population concerned,  
81 and virological properties of locally circulating variants.

82 Throughout the pandemic, mathematical models (Box 1) have proven useful both to better  
83 understand the epidemiological processes underlying SARS-CoV-2 outbreaks and to  
84 support public health decision-making. Modelling studies focusing on nosocomial risk in  
85 particular, although less publicized than those focusing on community risk, have addressed  
86 a broad range of epidemiological questions [8] and aided public health decision-making [9].  
87 However, epidemiological insights and public health recommendations from nosocomial  
88 SARS-CoV-2 models have not previously been reviewed or synthesized systematically.  
89 Here, we systematically search and review mathematical models developed to investigate  
90 SARS-CoV-2 transmission dynamics and control strategies in healthcare settings over the  
91 critical phase of the pandemic, present their main contributions, synthesize their conclusions,  
92 and discuss their limits.

### 93 **Methods**

94 We conducted a systematic search and review of mathematical/mechanistic models of inter-  
95 individual SARS-CoV-2 transmission within healthcare settings published up to February 14,  
96 2022. Details on the search, inclusion and exclusion criteria, screening process and data  
97 extraction are provided in the Supplementary File, and results are reported according to the  
98 PRISMA guidelines [10] (see Supplementary File).

### 99 **Results**

#### 100 **Model characteristics**

101 Overall, our search identified 1,431 studies, of which 59 were included after title, abstract  
102 and full-text screening (Suppl. Fig. S1 and Suppl. Table). Most (43/59) were posted in a  
103 publicly accessible pre-print server, with a median delay of 8 months (range: 1 to 24 months)  
104 between initial preprint posting and publication.

105 The majority of models were stochastic (85%; 50/59), and about half were agent-based or  
106 network models (53%; 31/59). At early stages of the pandemic, when testing resources were  
107 highly limited, most studies focused on surveillance and healthcare organization (Fig. 1A).

108 By comparison, impacts of PPE have been assessed less frequently, and vaccination  
109 strategies only began to be explored towards the end of 2020, as the first vaccines became  
110 available.

111 While models were mostly developed by teams from the USA, the UK, and other European  
112 countries, these models explored locations representing a wider range of countries  
113 worldwide (Fig. 1B). Acute care facilities and long-term care facilities were the main types of  
114 healthcare facilities considered, although this varied depending on the country of study (Fig.  
115 1C) and the subject addressed (Fig. 1D).

### 116 **Insights on SARS-CoV-2 acquisition routes and transmission risk**

117 Few studies have attempted to estimate the reproduction number of SARS-CoV-2 in  
118 healthcare settings, despite evidence that nosocomial and community risk may differ widely  
119 [11]. Estimates of nosocomial  $R_0$  range from 0.45 (0.36-0.56) in English acute care hospitals  
120 using a relatively simple approach [12] to 8.72 (5.14-16.32) in a French LTCF using a  
121 stochastic dynamic model accounting for imperfect surveillance [13]. Interestingly, in the  
122 latter study,  $R_0$  was estimated to drop to 1.33 (0.68-2.04) after introduction of control  
123 measures.

124 Several models have quantified the relative burden of SARS-CoV-2 infection and  
125 transmission among patients and HCWs over the course of the pandemic. HCWs were  
126 identified as being at high risk of occupational exposure to infection, either from colleagues  
127 or patients [14–16]. During the first wave in early 2020, they have been estimated to be the  
128 most important source of onward nosocomial transmission, both to patients and other HCWs  
129 [17,18]. However, other studies found that patient infection could result primarily from  
130 transmission from other patients [4,16,18].

### 131 **Insights on SARS-CoV-2 infection control**

#### 132 ***Evaluating and optimizing surveillance strategies***

133 Models have been widely used to assess and compare the epidemiological impacts of  
134 SARS-CoV-2 testing strategies. Because SARS-CoV-2 spreads extensively through pre-  
135 symptomatic and asymptomatic transmission [19,20], the identification of non-symptomatic  
136 infections is a key component of nosocomial IPC. Several studies have highlighted difficulty  
137 controlling outbreaks when targeting only symptomatic individuals for testing [21–28].  
138 Limited impact of only testing patients upon their admission has also been identified,  
139 suggesting that more thorough screening methods are required to limit SARS-CoV-2  
140 introductions from the community, visitors, HCWs or ancillary staff [24,27,29,30].

141 Many studies have evaluated the impact of routine testing of non-symptomatic individuals.  
142 The most universal finding is that more frequent testing leads to greater reductions in  
143 nosocomial transmission [12,14,21,23,24,30–40]. Similarly, increasing daily testing capacity  
144 has been found to limit nosocomial transmission [27,41]. In the context of limited test  
145 availability early in the pandemic, effective strategies identified for optimizing nosocomial  
146 outbreak detection include pooling samples via group testing [27] and distributing tests over  
147 several batches instead of using them all at once [42].

148 Modelling results are less consistent concerning which subpopulations to target for routine  
149 non-symptomatic testing. Many conclude that targeting HCWs is most effective  
150 [12,25,32,43], while others suggest targeting facility patients or residents [22,27,39].  
151 Divergence owes to underlying modelling assumptions on how patients and HCWs differ,  
152 regarding their infectiousness, susceptibility to infection, contact behaviour, and degree of  
153 interaction with visitors and other individuals in the community. For instance, testing staff  
154 proved more effective in a model of English care homes where the main source of SARS-  
155 CoV-2 introductions was staff members infected in the community [25]. Conversely, testing  
156 patients was more effective in models of a French rehabilitation hospital in which high rates  
157 of contact among ambulatory patients translated to high rates of patient-to-patient  
158 transmission [27,39]. In nursing homes, patient testing likely becomes increasingly important  
159 when visitors or other interactions with the community are permitted [33].

160 Lastly, in addition to testing frequency, studies have quantified the critical impact of the  
161 sensitivity and turnaround time of the test being used [24,28,30,32,33,37,38,44–47]. Several  
162 studies have identified that gains in turnaround time tend to outweigh gains in test sensitivity,  
163 explaining why rapid diagnostic tests (e.g. Ag-RDT) may be more effective than laboratory-  
164 based tests (e.g. RT-PCR) for routine non-symptomatic testing [23,25,32,39]. Conversely, if  
165 same-day test results are achievable, or if individuals effectively isolate while awaiting test  
166 results, more sensitive laboratory tests likely outperform rapid tests [33,34,44].

### 167 ***Evaluating impacts of personal protective equipment (PPE)***

168 Several studies have found that, when available, PPE use is highly effective for reducing  
169 infection risk among both HCWs and patients. Although predicted reductions in infection risk  
170 naturally depend on assumptions underlying PPE's impact on viral transmissibility, which  
171 vary considerably across studies and for which data are sorely lacking, several studies  
172 suggest that widespread PPE use remains a key SARS-CoV-2 prevention strategy, even  
173 when conferring comparatively low levels of protection [15,29,37,48–50]. By preventing  
174 infection, PPE use has also been shown to reduce HCW workplace absence [37] and  
175 workday loss [22]. Very few studies have tackled the question of who should be given priority  
176 to PPE access when in limited supply, although PPE has been shown to be particularly  
177 effective when accessible to all HCWs [48].

178 Regarding different types of PPE that may be used, Hüttel et al. [15] found hand sanitizer to  
179 be an effective means of reducing risk as a supplement to other strategies. Regarding  
180 timing, earlier introduction of PPE was found to allow a much more efficient response [22]  
181 and to enable prevention of large outbreaks [25]. However, further analyses suggest that the  
182 level of protection PPE confers can be occasionally overwhelmed in the context of large  
183 numbers of infected people in a room [51]. Finally, waning PPE adherence due to pandemic  
184 fatigue could significantly impact the efficacy of PPE-based interventions [52].

### 185 ***Evaluating and optimizing healthcare organization***



186 Many modelling studies have assessed the epidemiological impacts of healthcare facilities  
187 adapting their structures of care and workplace organization. Larger facilities have been  
188 found to be at greater risk of nosocomial SARS-CoV-2 outbreaks [43], and splitting facilities  
189 into smaller independent units has been shown to reduce the total number of infected  
190 individuals [36,48], except when transmissibility is high [53]. Forbidding visitors was  
191 identified as not having a significant effect on outbreak probability [25], except when infection  
192 prevalence among visitors' contacts in the community is higher than that of HCW community  
193 contacts [54].

194 Models have highlighted that rapid isolation of positive cases is an effective strategy for  
195 infection prevention [36,55,56]. Interestingly, models suggest that intermixing recovered  
196 individuals with potentially susceptible individuals could reduce outbreak size [32], and that  
197 sufficient spacing between patient beds is needed to limit transmission risk [36]. Results are  
198 less consistent regarding isolation upon admission. Models have highlighted the efficacy of  
199 isolating all newly admitted patients for a given duration [29] or while awaiting test results  
200 [12]. Conversely, others report no additional benefit of front-door screening or quarantine  
201 upon admission when other strategies are already in place [43,55].

202 Regarding staff organization, models have demonstrated benefits of cancelling HCW  
203 gatherings [57,58] and of forcing shorter and fewer patient-HCW interactions [51,58],  
204 although surprisingly this latter result was not confirmed by others [22]. Reducing between-  
205 ward staff sharing also seems to reduce both the number of wards with infected individuals  
206 [55] and the global reproduction number [37]. More complex staffing strategies have also  
207 shown potential benefits, like splitting staff into two teams that do not interact [59,60],  
208 synchronizing rather than staggering staff rotations [61], or immunity-based staffing [32,35],  
209 e.g. assigning recovered staff to infected patients [35]. Finally, admitting all COVID-19  
210 patients to specialized quarantine hospitals in which HCWs continuously resided for 1-to-2  
211 week-long shifts did not necessarily increase occupational HCW risk [62].

212 ***Evaluating vaccination strategies***

213 All models exploring vaccination found that it could help reduce COVID-19 morbidity and  
214 mortality, especially in LTCFs [23,28,31,33,52,63–67]. However, some studies also noted  
215 that vaccination benefits could be hindered by high levels of community SARS-CoV-2  
216 circulation [31,65] or by reduced adherence to contact precautions within facilities  
217 concomitant with vaccine rollout, for instance due to pandemic fatigue or risk compensation  
218 [52].

219 A major focus of these models has been evaluation of which groups of individuals to target  
220 or prioritize for vaccination in a context of limited vaccine availability, yielding sometimes  
221 inconsistent results. Some found that LTCF residents should be prioritized over staff,  
222 especially in LTCFs with low adherence to IPC measures [33,52]. Conversely, staff  
223 vaccination was shown to be particularly effective for decreasing the overall attack rate,  
224 especially in the absence of a testing protocol [64]. Targeting staff for vaccination may also  
225 be preferable when the risk of virus importation from the community is high [31]. Finally, it  
226 has been shown that vaccine rollout should first target staff members most exposed to  
227 potential COVID-19 patients (e.g. staff from emergency departments) [63].

228 It should be noted that the conclusions reached by these models depend strongly on  
229 modelling assumptions underlying vaccine action. Across models, assumed mechanisms  
230 related to vaccination effectiveness included one or several of the following: a reduction in  
231 acquisition risk, a reduction in symptom risk, and a reduction in the infectiousness of infected  
232 vaccinated individuals. For instance, it was shown that if a vaccine only reduces symptom  
233 risk, then increasing vaccination among nursing home staff leads to an increase in the  
234 proportion of asymptomatic infections among staff, which subsequently leads to increased  
235 infection risk for residents [23]. Additionally, no model considered vaccine impact over the  
236 long-term, which is particularly relevant in the context of waning immunity and the  
237 emergence of novel variants with vaccine-escape properties.

238 **Discussion**

239 Mathematical models have become ubiquitous tools to help understand the dynamics of  
240 infectious disease outbreaks and to support public health decision-making. Here, we have  
241 reviewed how models have helped to inform COVID-19 risk management in healthcare  
242 settings, in particular by providing a better understanding of nosocomial transmission  
243 dynamics and control strategy effectiveness.

244 The generation of *in silico* evidence to inform infection control strategies has been the  
245 leading motivation for nosocomial SARS-CoV-2 transmission modelling. Although real-world  
246 evidence collected during randomized controlled trials is the gold-standard, such data are  
247 extremely difficult to generate in the context of a rapidly evolving epidemic. Beyond the  
248 obvious costs and time involved, great heterogeneity in population characteristics and  
249 exposure risk across different healthcare settings means that a large number of centres  
250 must be enrolled to achieve sufficient cluster randomisation. Several high-impact  
251 randomized controlled trials have nonetheless been successfully conducted in healthcare  
252 settings despite these challenges, in particular to evaluate COVID-19 vaccines, therapies  
253 and pre- or post-exposure prophylactic agents [68–71]. However, trials evaluating impacts of  
254 common IPC interventions, including surveillance testing, PPE and healthcare  
255 reorganization, are scarce [72,73].

256 In this context, mathematical modelling approaches have been particularly helpful to  
257 investigate critical IPC questions in (near) real-time, since they allow for the simulation of  
258 diverse scenarios at relatively high speed and low cost, while accounting for all available  
259 knowledge and uncertainty at a given place and time. Model-based evaluations also allow  
260 for levels of granularity in intervention arms that may be infeasible in real trial designs. Our  
261 review highlights the range of modelling studies published before the end of 2020, at a time  
262 when the scientific and medical communities were in particularly great need of evidence to  
263 inform optimal allocation of limited infection prevention resources, including RT-PCR tests,  
264 face masks and, later, vaccines.

265 However, two common means of SARS-CoV-2 transmission prevention with important  
266 implications for the field have been notably under-addressed. First, modelling studies on the  
267 relative impact of different types of face masks (e.g. surgical masks, N95 respirators) are  
268 scarce [74], tied to a lack of precise data on how they impact viral transmissibility, as well as  
269 their potential indirect roles as transmission vectors. Second, although ubiquitous in practice  
270 at various stages of the pandemic, explicit social distancing interventions have rarely been  
271 assessed [22,39]. This is probably because accurate modelling of social distancing requires  
272 fine-scaled simulation of inter-individual contact networks, typically using an agent-based  
273 approach, which is beyond the scope of most models. When faced with both epistemic  
274 uncertainty and a need for relative computational simplicity, modelers may be reluctant to  
275 include and formalize specific interventions that require arbitrary, highly sophisticated and/or  
276 potentially wrongheaded assumptions about their mechanistic impacts on SARS-CoV-2  
277 transmission. Instead, a common modelling strategy has been to include generic non-  
278 pharmaceutical interventions that simply reduce the viral transmission rate, and which are  
279 assumed to represent any combination of basic infection prevention interventions, including  
280 face masks, gloves, gowns, face shields, hand hygiene or social distancing.

281 Relative to the evaluation of infection control strategies, modelling studies have more rarely  
282 focused on the estimation of epidemiological parameters using statistical inference. In  
283 particular, in the event of the sudden emergence of a novel infectious disease,  $R_0$  estimation  
284 is essential for epidemic forecasting and emergency response planning, and relies largely on  
285 mathematical modelling approaches. Although estimates of  $R_0$  quickly became available for  
286 SARS-CoV-2 across various community settings in early 2020, [75], estimates specific to  
287 healthcare settings remain scarce. Yet there is a great need for robust estimates across  
288 diverse settings, as underlying levels of epidemic risk vary substantially across facilities due  
289 to their intrinsic heterogeneity (e.g. types of care provided, population sizes, contact  
290 behaviour of these populations). For instance, assuming  $R_0=3.5$  in the community, Temime  
291 et al. [11] estimated that nosocomial  $R_0$  could range from 0.7 to 11.7, depending on the type

292 of ward and the density of contacts among and between patients and HCWs. This  
293 heterogeneity in nosocomial  $R_0$  is consistent with the range of estimates derived from  
294 models described in this review [12,13], and has critical implications, informing which  
295 facilities and populations are most at risk for explosive outbreaks and thus most in need of  
296 urgent infection control measures.

297 This lack of evidence likely stems from both data limitations and remaining uncertainty about  
298 the relative importance of precise paths of transmission (e.g. through direct person-to-person  
299 contact; transient viral carriage on hands, garments or shared medical devices; stagnant air  
300 in poorly ventilated spaces). Particularly early in the pandemic, nosocomial COVID-19 data  
301 came primarily from contexts of emergency outbreak management rather than routine data  
302 collection through stable surveillance systems. For future waves of SARS-CoV-2 and other  
303 infectious diseases, the estimation of epidemiological parameters may be made easier by  
304 harnessing large databases that systematically gather patient and HCW tests results,  
305 administrative data and healthcare exposures across diverse healthcare facilities over time.

306 Researchers have faced significant challenges when developing SARS-CoV-2 transmission  
307 models. First, data limitations, particularly early in the pandemic, forced many modelers to  
308 make assumptions that oversimplify healthcare facility structure, population behaviour and  
309 SARS-CoV-2 transmission dynamics, limiting the applicability of some results to real-world  
310 settings. Second, the shifting epidemiological landscape – characterized not only by the  
311 rapid spread of SARS-CoV-2, but also rapid change in population behaviours, sudden  
312 resource shortages, consecutive changes in public health recommendations, rapid approval  
313 of novel diagnostics, therapies and vaccines, and the successive emergence of distinct  
314 variants of concern – required researchers to continually adapt their models in order to  
315 remain useful, with relevant data required to parameterize these updates often lagging  
316 behind.

317 Greater interdisciplinarity will be required to maximize the utility of mathematical modelling in  
318 the future. More direct lines of contact between modelers, hospital infection control teams,

319 clinicians and decision-makers should guide modelers in their research. First, this may help  
320 to steer studies towards the questions that are most clinically relevant, as informed by the  
321 needs and issues faced in real clinical settings. Second, this may help modelers to evaluate  
322 strategies that are feasible in practice, considering logistical constraints such as workforce or  
323 equipment availability and hospital structure. Third, these discussions may inspire modelers  
324 to account for outcomes beyond transmission risk and infection burden, such as cost-  
325 effectiveness or mental health. Indeed, interventions such as visitor restrictions or staff re-  
326 organization can have a great impact on the social isolation of patients or workload of  
327 HCWs, which is difficult to take into account explicitly in mathematical models. Cost-  
328 effectiveness is increasingly considered in modelling studies; for instance, several studies  
329 have quantified the health-economic efficiency of frequent non-symptomatic testing  
330 [12,24,38,39,45]. However, more frequent estimation of health-economic outcomes may  
331 increase their usefulness for decision-makers, who must balance the competing priorities of  
332 maximizing population health and minimizing monetary cost. Finally, increased  
333 communication across disciplines may facilitate more timely sharing of modelling results to  
334 those who may benefit from them most, including infection control teams and hospital  
335 administrators. The use of social media and the surge in posting of articles on pre-print  
336 repositories during the COVID-19 pandemic have helped to facilitate the timely sharing of  
337 results, but there remains an onus on academic publishers to ensure a timely peer review  
338 process so that modelling results are shared quickly enough to maximize their impact.

339 This review has several limitations. First, we chose to exclude all statistical, mathematical, or  
340 computational models not including inter-individual SARS-CoV-2 transmission.  
341 Consequently, other types of models such as physical or biomechanical models of airborne  
342 transmission were excluded [76–78]. Second, we excluded articles posted on public archives  
343 such as arXiv, medRxiv or biorXiv [79], which are not subject to peer review and can be  
344 difficult to track. Although we did include some preprints in our review, we were unable to  
345 systematically explore these archives. Third, we may have missed articles published in

346 journals not referenced in PubMed (e.g. computer science or mathematical journals).  
347 However, since our focus was on epidemiological insights and public health  
348 recommendations, we do not believe that this significantly impacted our main findings.

### 349 **Conclusion**

350 Often developed in the face of great epidemiological uncertainty, mathematical models have  
351 come to form a rich evidence base describing how SARS-CoV-2 spreads in healthcare  
352 settings and informing which nosocomial COVID-19 control strategies are optimal, in  
353 particular with regards to healthcare reorganization and the allocation of limited supplies of  
354 PPE, diagnostic testing and vaccines. Into the future, epidemiological models may continue  
355 to inform control strategies for outbreaks of SARS-CoV-2 and other viral respiratory  
356 pathogens, but increased collaboration should be sought between modelers, hospital  
357 infection control teams, clinicians, and public health decision-makers to help maximize their  
358 utility.

### 359 **Conflict of interest**

360 Authors report no conflict of interest.

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371 **Author contributions**

372 LO, LT, SK conceived the study, LO and LT acquired the funding. Screening of the articles  
373 was performed by DRMS, SC, GS, SJ, KJ, LO and LT. Data extraction and analysis were  
374 performed by DRMS, SC, GS, SJ, LO and LT. DRMS, SC and TP rendered figures and  
375 statistics. All authors contributed to writing.

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662

663 **Figure captions:**

664 ***Box 1: Mathematical models of SARS-CoV-2 transmission in health care settings***

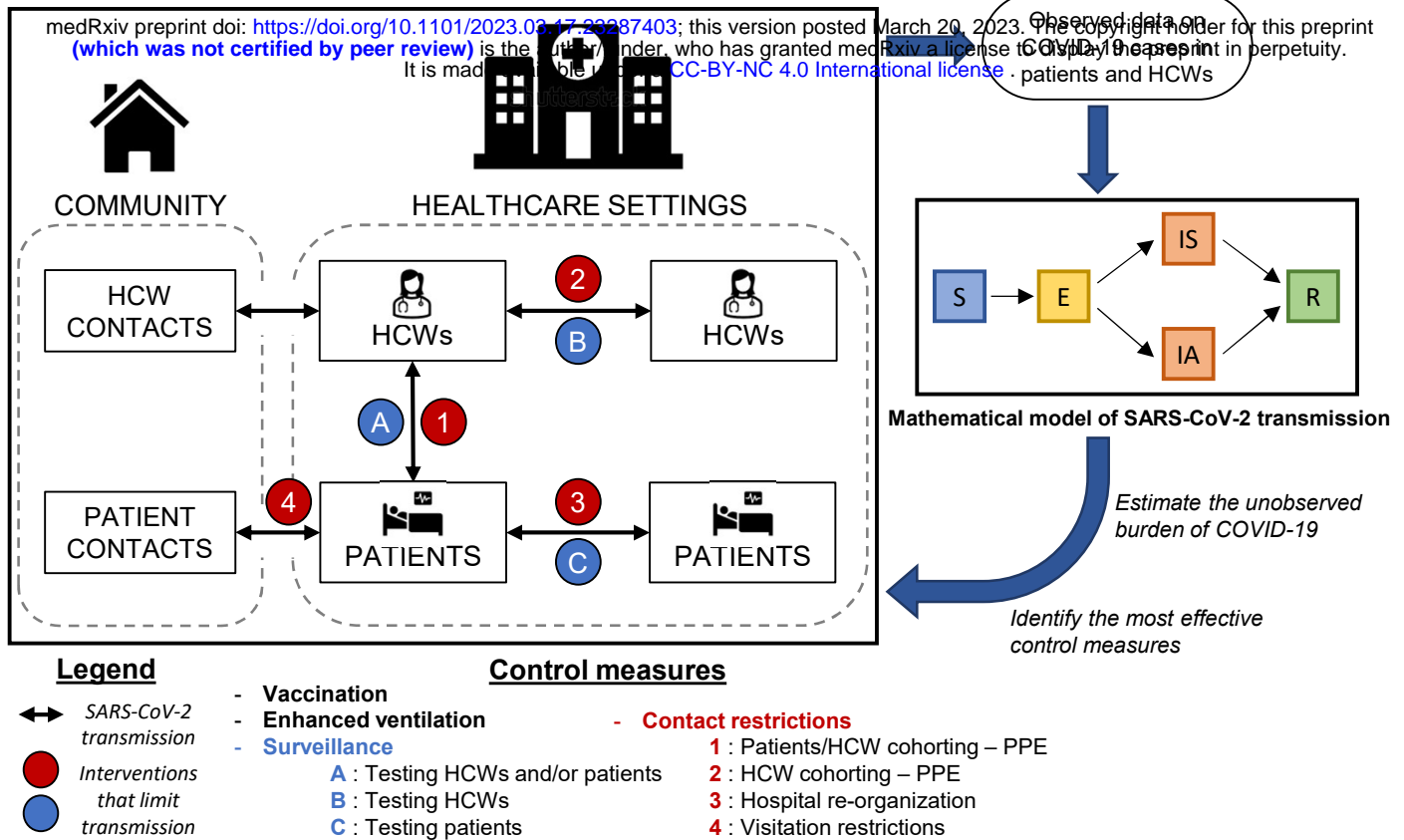
665 ***Figure 1: Characteristics of identified models of SARS-CoV-2 transmission within***  
666 ***healthcare settings.*** (A) Cumulative number of modelling studies made accessible per  
667 month since March 2020, stratified by primary focus(es) addressed. The date used is the  
668 date of first publication, either on a public archive or in a journal. Studies addressing several  
669 subjects are counted several times. (B) Geographical distribution of countries on which the  
670 modelling is focused. (C) Distribution of modelled healthcare settings per studied country.

671 (D) Distribution of addressed subjects, depending on the type of healthcare setting. Studies

672 addressing several subjects are counted several times.

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Mathematical models are theoretical constructs that mechanistically formalize the dynamic processes underlying SARS-CoV-2 transmission. A typical model splits the individuals present in a healthcare facility into sub-populations, including one or more categories of patients (or residents) and HCWs. Mathematical or statistical tools are used to describe the natural history of infection through the definition of different infection states or “compartments”. For instance, in the specific case of SARS-CoV-2, which is characterized by an incubation period subsequent to exposure and the acquisition of (partial) immunity after infection, the main compartments considered are: Susceptible to infection (S), Exposed to infection or incubating (E), Infectious (I), and Recovered or immunized (R). As a large share of infectious individuals may be asymptomatic, the I compartment is often subdivided into asymptomatic (IA) and symptomatic (IS) compartments. Various other sources of heterogeneity may also be considered, including different levels of viral shedding among infectious individuals, or different trajectories of care among symptomatic individuals (e.g., isolation, mechanical ventilation, admission to intensive care, death). Specific contact patterns between individuals of different sub-populations and infection statuses can further be accounted for through the definition of contact matrices.

Compartmental models are most frequent, but agent-based models (also known as individual-based models) are another common formalism, in which each unique individual in the population is explicitly modelled. This enables more detailed integration of heterogeneity in contact patterns, disease progression, transmission risk and other epidemiological processes. Models can further be categorized as either deterministic or stochastic. In deterministic models, there is no randomness in epidemiological processes, and a particular set of initial conditions always results in identical outbreaks. By contrast, in stochastic models, it is possible to account for randomness in the parameters or processes included, resulting in different outbreak trajectories each time the model is run. Stochasticity is particularly relevant in models of healthcare settings, where population sizes are small and randomness can have a strong impact on outbreak dynamics.

Models are used for a variety of purposes. They are widely used to simulate virus transmission in specific settings and populations, allowing for the quantification of virus burden in particular epidemiological scenarios (e.g. after the introduction of a novel SARS-CoV-2 variant into a hospital via newly admitted patients, short-stay visitors, or members of staff infected in the community). Models are also used to enable the *in silico* assessment of public health interventions through the mechanistic implementation of interventions (e.g. testing, isolation, PPE provisioning, contact restrictions, vaccine deployment). Intervention impact can then be evaluated by simulating counterfactual outbreaks with and without the intervention in place. Finally, models are key to analysing reported data from real outbreaks (e.g. time series data, individual line lists of SARS-CoV-2 cases), accounting not only for unobserved processes (e.g., virus transmission) but also incomplete infection data, whether due to the presence of asymptomatic infections, imperfect reporting, or limited surveillance capacity. This allows for the retrospective assessment of true disease burden from a given outbreak (e.g., cumulative infection incidence) as well as estimation of important epidemiological parameters such as  $R_0$ , the basic reproduction number, which describes the average number of secondary cases caused by an index case in an immunologically naïve population.  $R_0$  is particularly helpful to understand the epidemic potential of an emerging pathogen, though its value may vary across distinct sub-populations and settings, such as particular groups of patients and HCWs in particular healthcare facilities.

