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Research paper

Social network-based cohorting to reduce the spread of SARS-CoV-2 in secondary schools: A simulation study in classrooms of four European countries

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ABSTRACT

Background: Operating schools safely under pandemic conditions is a widespread policy goal. We analyse the effectiveness of classroom cohorting, i.e., the decomposition of classrooms into smaller isolated units, in inhibiting the spread of SARS-CoV-2 in European secondary schools and compare different cohorting strategies.
Methods: Using real-world network data on 12,291 adolescents collected in classrooms in England, Germany, the Netherlands, and Sweden in 2010/2011, we apply agent-based simulations to compare the effect of forming cohorts randomly to network-based cohorting. Network-based cohorting attempts to allocate out-of-school contacts to the same cohort to prevent cross-cohort infection more effectively. We consider explicitly minimizing out-of-school cross-cohort contacts, approximating this information-heavy optimization strategy by chained nominations of contacts, and dividing classrooms by gender. We also compare the effect of instructing cohorts in-person every second week to daily but separate in-person instruction of both cohorts.
Findings: We find that cohorting reduces the spread of SARS-CoV-2 in classrooms. Relative to random cohorting, network-based strategies further reduce infections and quarantines when transmission dynamics are strong. In particular, network-based cohorting inhibits superspreading in classrooms. Cohorting that explicitly minimizes cross-cohort contacts is most effective, but approximation based on chained nominations and classroom division by gender also outperform random cohorting. Every-second-week instruction in-person contains outbreaks more effectively than daily in-person instruction of both cohorts.
Interpretation: Cohorting of school classes can curb SARS-CoV-2 outbreaks in the school context. Factoring in out-of-school contacts can achieve a more effective separation of cohorts. Network-based cohorting reduces the risk of outbreaks in schools and can prevent superspreading events.
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1. Introduction

Schools facilitate the spread of communicable diseases by bringing together large numbers of interconnected individuals. To safely operate schools in pandemic conditions, strategies that lower the risk of in-school infection are needed to reduce the spread of SARS-CoV-2. Specifically, decomposing the student population into smaller isolated units may reduce the risk of large infection clusters. While research on social distancing measures in schools is still scant, [1] emerging evidence from modelling studies for schools in the US suggests that reducing group size can indeed help reduce infections [2–9]. However, insights from these studies are not readily applicable to the European context characterized by different structures of in-school instruction. Unlike in the US, in most European countries, schools are organized in classrooms of 20-40 students and most courses are taught to this fixed set of students. In a model designed for the UK epidemic that included schools among other societal layers, part-time rota systems with reductions of 50% of the student body were associated with reductions in community transmission rates [10]. However, this study did not explicitly focus on transmission processes in schools, so there is no scientific guidance on *how* to best divide classrooms to avoid the spread of infections between groups so far. To fill this gap, we examine the effectiveness of different strategies to divide classrooms in curbing the spread of SARS-CoV-2 in European schools.

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Research in Context

Evidence before this study

We searched PubMed, medRxiv, and Social Science Research Network for peer-reviewed articles and preprints published up to April 5th 2021 using the terms ("SARS-CoV-2" OR "Covid-19") AND ("school") in the abstract and title, and in another search using the terms ("SARS-CoV-2" OR "Covid-19") AND ("school") AND ("modeling" OR "model") in the full text. There are eight preprint modeling studies for the US context assessing the effectiveness of cohorting for preventing in-school Covid-19 outbreaks. Another study models the effect of school closures and part-time instruction on UK community transmission rates but does not consider cohorting. Therefore, there is no scientific guidance on classroom cohorting and on how to divide classrooms in order to reduce SARS-CoV-2 transmission in European schools or contexts in which schools are organized similarly. Furthermore, none of the studies investigate real-world classroom contact networks and their consequences for the effectiveness of cohorting.

Added value of this study

This is the first agent-based network model on SARS-CoV-2 transmission in schools that uses empirically observed contact networks; it also is the first modeling study of classroom cohorting and SARS-CoV-2 transmission in European schools. It shows that classroom cohorting can help contain outbreaks and that accounting for contact networks can increase the effectiveness of cohorting further. Our study therefore presents hitherto unavailable scientific guidance on classroom cohorting as a social distancing measure in European secondary schools.

Implications of all the available evidence

Cohorting of school classes reduces the risk of school-based SARS-CoV-2 outbreaks, especially large ones. If schools use cohorting, they should consider students' contact networks and allocate students who meet after school to the same cohort. This can inhibit infections across cohorts and prevent super-spreading. In-person instruction of cohorts that takes place only every other week can curb outbreaks more effectively than instruction of all cohorts on the same day.

In line with the definition of the Centre for Disease Control and Prevention, [11] we term the process of dividing classes *cohorting* and the resulting separate groups *cohorts*. We consider cohorting strategies that split classrooms into two cohorts of approximately equal size. We limit our analysis to bisecting classrooms because divisions into larger numbers of (smaller) cohorts are likely to exceed schools' resources. Cohorting both facilitates physical distancing within the classroom and reduces the number of students exposed to an infectious classmate, which can moderate the size and reach of an outbreak.

Separate instruction of cohorts prevents transmission between cohorts *within* school, but contacts between cohorts *outside* of school can also lead to cross-cohort infections. Therefore, the effectiveness of cohorting can likely be improved by accounting for out-of-school contact networks among students and constructing cohorts with as little cross-cohort out-of-school contact as possible. However, implementing corresponding cohorting strategies requires information on actual student contact networks and has not been assessed in previous research. We compare the effect of such *network-based* cohorting strategies to strategies that do not consider out-of-school contact.

2. Methods

We compare four cohorting strategies to a baseline scenario with undivided classrooms. We first consider *random cohorting*, which randomly divides classrooms into two equally-sized cohorts. Unlike our remaining strategies, random cohorting does not account for students' out-of-school contacts, so contacts that span cohorts can still serve as transmission channels. By contrast, our first network-based strategy splits cohorts by gender, exploiting strong gender segregation in adolescents' networks, [12,13] so that many resulting out-of-school contacts are within rather than between cohorts. This *gender-split cohorting* strategy is easy to implement, but cross-gender friendships or romantic relationships may undermine its efficiency. The second network-based strategy, *optimized cohorting,* explicitly uses information on students' self-reported out-of-school contacts to form cohorts that minimize the number of cross-cohort contacts. By definition, this strategy produces the cleanest separation of cohorts and should thus be most effective in preventing cross-cohort infection. However, it requires teachers to know students' out-of-school contact networks and optimize cohorts accordingly, and is thus hard to implement in practice. As a third network-based strategy, we therefore propose a *network chain cohorting* approach that uses an easy-to-implement in-class nomination procedure to approximate the optimization strategy. In this strategy, an initial student who is well-connected—such as a class representative—names all of her in-class out-of-school contacts, and the resulting set of students forms the basis for the first cohort. Subsequently, the listed out-of-school contacts name *their* out-of-school contacts, who also become members of the first cohort. The process continues until half of the classroom is allocated to the first cohort, and the remaining students form the second cohort. Table 1 provides an overview of the cohorting strategies, and the Supplementary Appendix provides more information on the technical implementation in our simulations.

For an example classroom from our data set, Fig. 1 demonstrates both how the four different strategies induce different allocations of students to cohorts and how they limit cross-cohort out-of-school contacts. Under random cohorting, there are many cross-cohort contacts. By contrast, gender-split and network chain cohorting produce fewer cross-cohort ties and optimized cohorting even succeeds in perfectly separating cohorts in this example classroom.

To assess the classroom transmission of SARS-CoV-2 when these cohorting strategies are implemented, we use real-world student network data from the first wave of the Children of Immigrants Longitudinal Study in Four European Countries (CILS4EU) project [14,15]. The data were collected in 2010-2011 and provide information on 14-15-year-old students from England, Germany, the Netherlands, and Sweden. Our sample consists of 507 classrooms populated by

Table 1
Overview of cohorting strategies.

Strategy	Description
Random cohorting	Two cohorts are formed by randomly allocating half of the students to each cohort.
Gender-split cohorting	One cohort consists of boys, one of girls. Students from the smaller cohort (i.e., the underrepresented gender) are reallocated until both cohorts have the same size. (See Supplementary Material, section B, for variations.)
Optimized cohorting	Two equally-sized cohorts are formed to minimize the number of cross-cohort out-of-school contacts.
Network chain cohorting	An initial student names all of her out-of-school contacts, who themselves name their out-of-school contacts, etc., until the resulting set of students comprises half of the classroom. This set of students forms the first cohort, the remainder the second cohort.

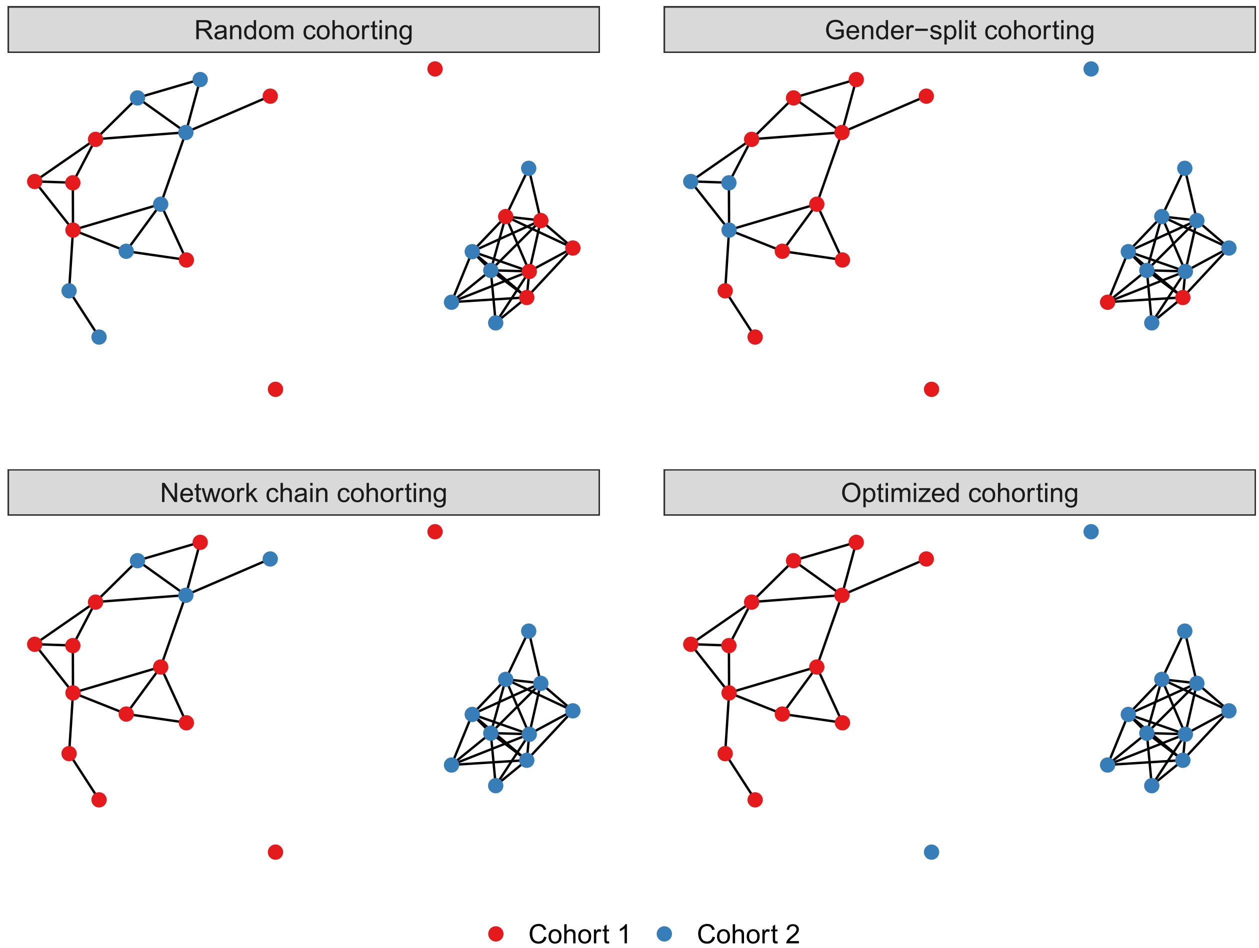

Fig. 1. Cross-cohort out-of-school ties for different cohorting strategies in an example classroom from the CILS4EU data. Nodes represent students and ties among nodes represent out-of-school contacts with classmates. Colors indicate the cohort to which students have been allocated. Cohorts have the same size.

12,291 students. We capture out-of-school interaction by an indicator assessing the classmates a student "often spend[s] time with outside school". Students could nominate as many of their classmates as they wanted. Whenever one student named another, we code an out-of-school contact between this pair of students. The median number of out-of-school contacts is three and the average is 3·15 classmates. Further information on the data is provided in the Supplementary Material.

We use these real-world social network data to provide agent-based simulations on the transmission of SARS-CoV-2 within classrooms. We simulate transmission dynamics separately for each classroom and each cohorting strategy, repeating simulations 2000 times and reporting averages across these runs. The agent-based model is summarized in Fig. 2. Each simulation starts with one randomly infected seed-node student who, once infectious, can infect her cohort members in school and her out-of-school contacts. *In-school contact* with other cohort members occurs only Monday to Friday and only if a cohort is instructed in-person on that day. We consider two modes of in-person instruction: Either both cohorts are instructed in-person on each school day (using multiple classrooms or different schedules), or each cohort is instructed in-person every second week. *Out-of-school contact* can take place on every day of the week. We assume a daily probability of out-of-school-contact of 20% for each contact. This corresponds to an average of 4·2 out-of-school interactions per week for the median student, who has three out-of-school contacts, but we find similar results for daily contact probabilities as low as 5% (see Supplementary Material section E).

In-school or out-of-school contact with an infectious student results in infection with a probability that depends on the general baseline infection risk, on how risky the specific interaction is, and the infected student's infectiousness. We consider variation in (daily) baseline probabilities of infection upon contact between 5 and 25%. This corresponds to secondary attack rates of 4%-14% and thus captures most of the variation reported in the literature, [1,16–23] including estimates for more transmissible variants such as B.1.1.7 [21–23]. To obtain the total probability of infection upon interaction, this baseline probability is multiplied by the riskiness of the specific interaction and by the infected student's infectiousness. Out-of-school interactions are defined as high-risk, yielding a multiplication factor of 100%. We also assume that 25% of in-school interactions are high-risk because of physical proximities in the classroom. The remaining 75% of in-school interactions are low-risk, and the baseline probability is reduced to 20% of its original value to account for this lower risk. (Results are robust to other plausible parameter values, see Supplementary Material section F). To account for overdispersion in the transmission of SARS-CoV-2, [24–26] we model individual infectiousness to have a mean of 100%, but to vary stochastically through Gamma distributions, so that about 80% of all infections are caused by about 20% of the infectious students. Individual students' trajectories of Covid-19 are further characterized by whether an infection is subclinical or clinical, the relative infectiousness of subclinical infections, the length of the latency period, the length of the infectious period, and the time until symptom onset given a clinical infection. We rely on estimates for these parameters from previous

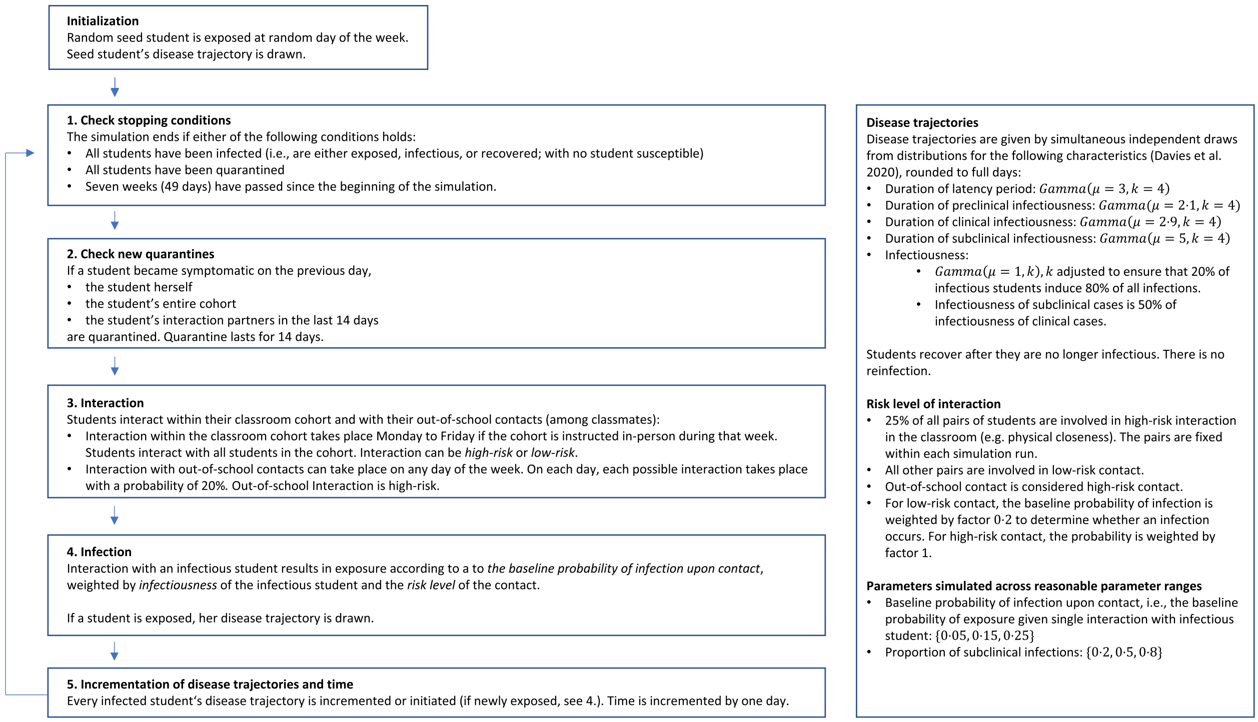

Fig. 2. Simulation model for transmission of SARS-CoV-2 within classrooms.

age-dependent models of SARS-CoV-2 transmission to model the distribution of these characteristics across students [27] (see Fig. 2 for a summary).

When the seed node has infected additional students, they can in turn infect their cohort members and out-of-school contacts, potentially triggering larger outbreaks. Once a student becomes symptomatic, quarantines prevent further transmission: We assume that all members of the symptomatic student's cohort and all students involved in her out-of-school interactions in the last 14 days are quarantined on the next day. Quarantine lasts for 14 days. Simulations end when all students have been infected or quarantined, or when seven weeks have passed (capturing the effect of school holidays). In the model, the spread of SARS-CoV-2 within classrooms is fully determined by the observed network of contacts and the (stochastic) nature of each student's trajectory of Covid-19. Therefore, there is no need to adjust for additional covariates or confounders when interpreting our epidemiological outcomes.

To depict a wide range of estimates from recent research on Covid-19 symptoms in adolescents, [27–32] we investigate proportions of clinical cases between 20% and 80%. Jointly with the baseline

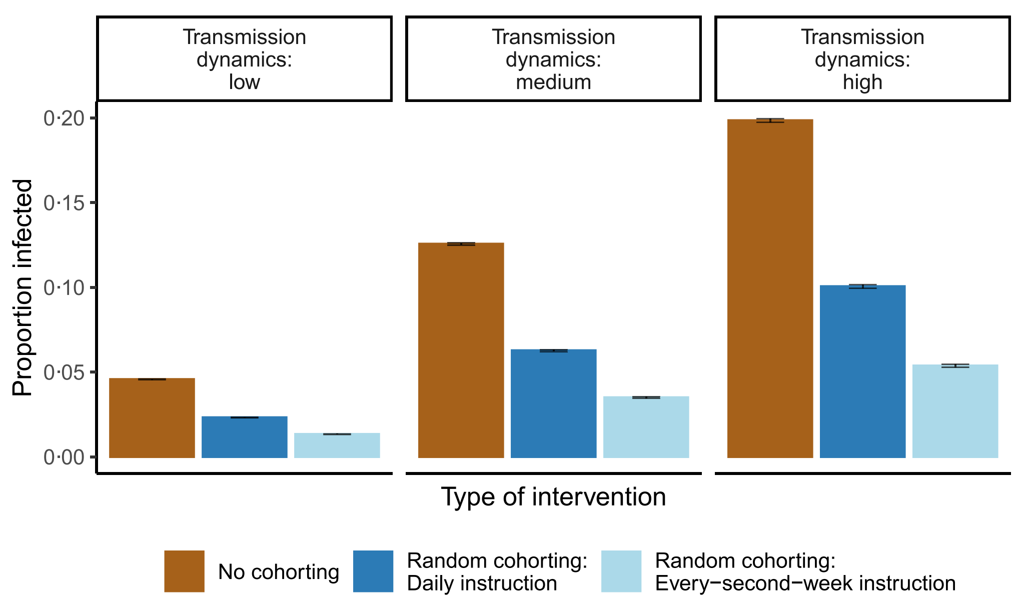

Fig. 3. Average proportion of infected students in case of no cohorting and two types of random cohorting. Proportions and 95% confidence intervals. Results across entire parameter space are in Fig. S1.

probability of infection, which our simulations vary between 5% and 25%, the proportion of subclinical infections shapes overall transmission dynamics (because infections and transmissions go unnoticed if they are subclinical and can thus trigger larger outbreaks). In the analysis, we combine these two characteristics and show results for three scenarios: *low transmission dynamics*, characterized by a low baseline probability for infection (5%) and a low proportion of subclinical cases (20%), *medium transmission dynamics* (probability for infection = 15%, proportion of subclinical cases = 50%), and *high transmission dynamics* (probability for infection = 25%, proportion of subclinical cases = 80%). In the Supplementary Material, we show results across all combinations of parameter values and provide additional technical details on the agent-based model.

2.1. *Role of the funding source*

The authors received no specific funding for this work.

3. Results

We first compare random cohorting to no cohorting. Fig. 3 shows the average proportion of infected students across all classrooms for both scenarios, differentiating random cohorting with either every-second-week instruction or with separate daily instruction of both cohorts. Independent of transmission dynamics, random cohorting with daily instruction of both cohorts reduces infections by about 50% compared to no cohorting. Random cohorting with in-person instruction every second week leads to a further reduction of about 50% relative to daily instruction because it allows in-school transmission in only one rather than both cohorts each week. In all settings, infections strongly depend on transmission dynamics, with a much larger proportion of students infected when transmission dynamics are high than when they are low.

Fig. 4 demonstrates that network-based cohorting is more effective than random cohorting in separating cohorts in terms of out-of-school contacts. It shows the distribution of the average number of cross-cohort contacts across classrooms for the four different cohorting strategies described in Table 1. The optimization strategy results in the lowest number of cross-cohort ties, with an average of 3·5 cross-cohort ties per classroom, 17% of the 20 cross-cohort ties under random cohorting. The gender-split and network chain strategy produce an average of 11·4 and 8·5 cross-cohort ties, respectively, which corresponds to 57% and 42% of the cross-cohort ties under random cohorting.

In Fig. 5, we show how the different cohorting strategies affect three epidemiological outcomes in our agent-based simulations: the proportion of outbreaks that spread across cohorts, the proportion of infected students across the entire classroom, and the proportion of students quarantined. For quarantines, a given proportion of clinical infections always implies an (average) minimum share of students quarantined independent of cohorting strategy. If, for example, 80% of all infections are clinical cases, 80% of seed nodes eventually become symptomatic, triggering quarantine in their cohort (i.e., half of the classroom) and thus inducing a minimum of 40% of quarantined students on average. For better comparability across strategies, Fig. 5 therefore shows the *excess proportion quarantined* up and above this minimum share. The total proportion quarantined is the sum of the excess proportion quarantined and the minimum share quarantined. The latter is indicated by the numbers above the quarantine bars in Fig. 5. Results are aggregated across classrooms; country- and classroom-level results are similar and presented in the Supplementary Material (sections C and G).

The top row of Fig. 5 shows that the frequency of SARS-CoV-2 spreading to the second cohort differs between cohorting strategies. Across all scenarios, gender-split, network chain and optimized cohorting outperform random cohorting, with optimized cohorting performing best throughout. Gender-split cohorting falls about halfway in between random and optimized cohorting and network chain cohorting is somewhat more effective. When transmission dynamics are higher, infections of the second cohort are more frequent for all cohorting strategies and differences between the cohorting strategies tend to be larger.

The effectiveness of the cohorting strategies generally follows the same order for the proportion of students infected and quarantined. For two reasons, however, differences between the cohorting strategies are smaller for these epidemiological outcomes than for the spread between cohorts. First, a transmission to the second cohort does not necessarily result in a larger outbreak and corresponding additional infections or quarantines within that cohort. Second, despite the fact that out-of-school contacts carry a higher

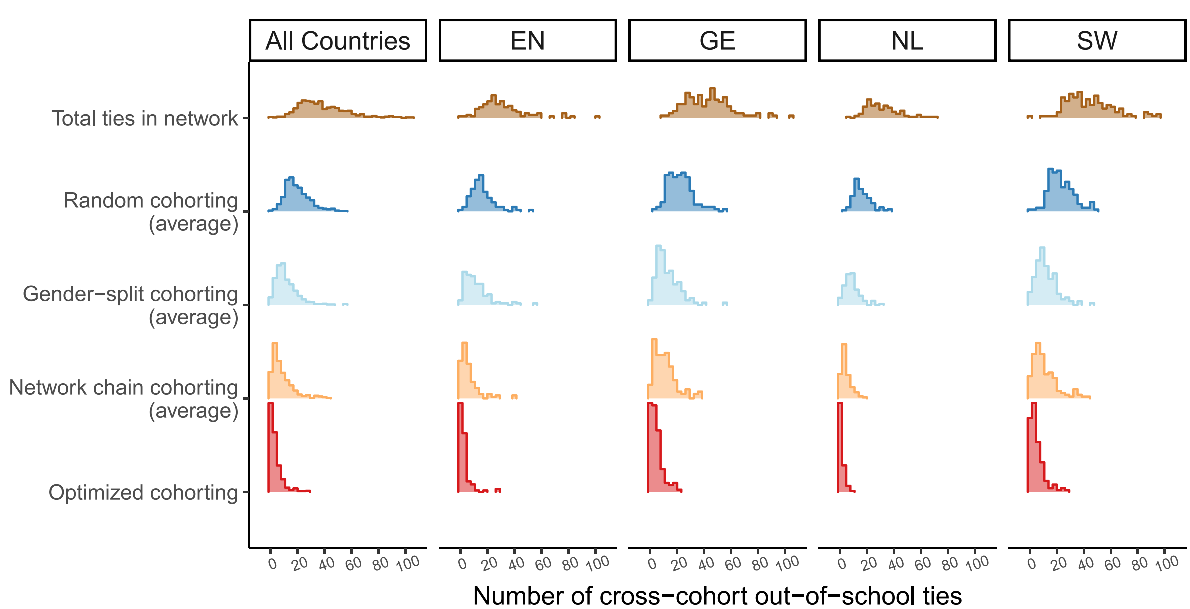

Fig. 4. Total number of ties between classmates in the out-of-school contact network and (average) number of cross-cohort ties for different cohorting strategies across all classrooms.

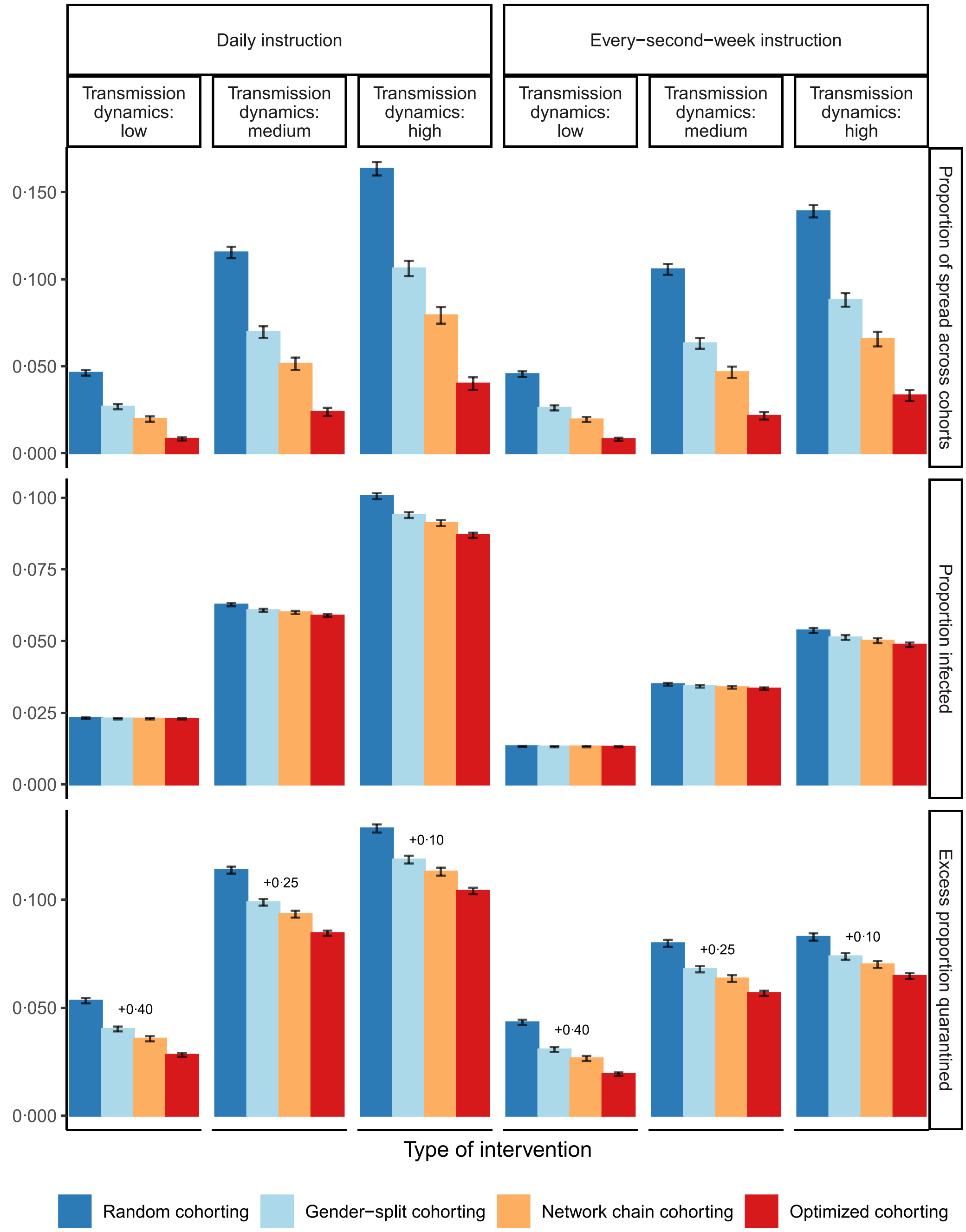

Fig. 5. Epidemiological outcomes of different cohorting strategies: Proportion of outbreaks spreading to the second cohort, proportion of students infected, and excess proportion of students quarantined. Proportions and 95% confidence intervals. Numbers above excess proportion quarantined indicate proportion to be added to obtain total proportion quarantined (+ 1/2 of proportion clinical). Results across entire parameter space are in Fig. S2.

transmission risk on average, in our model most infections between classmates occur through *in-school* interaction. This is because within-school contacts are much more frequent than out-of-school contacts. Therefore, a substantial baseline proportion of quarantines and infections are determined by within-cohort transmission dynamics rather than by cross-cohort infection.

As the middle row of Fig. 5 shows, differences between cohorting strategies are small for the proportion of infected students when transmission dynamics are low or medium. Under low transmission, the proportion of infections is independent of the cohorting strategy because outbreaks die out quickly even when they spread to the second cohort. By contrast, network-based cohorting strategies reduce the overall proportion of infected students substantially when transmission dynamics are high. Under these conditions, a transmission to the second cohort can result in a large outbreak in that cohort. Effective cohorting prevents this by successfully isolating cohorts. In-person instruction every second week both decreases the number of infected students and reduces the differences between cohorting strategies because it creates a cool-down period that frequently prevents onward transmission in the second cohort.

The bottom row of Fig. 5 indicates that network-based cohorting notably reduces the proportion of quarantined students under all conditions, even when transmission dynamics are low or instruction only takes places every second week: For cross-cohort infections to

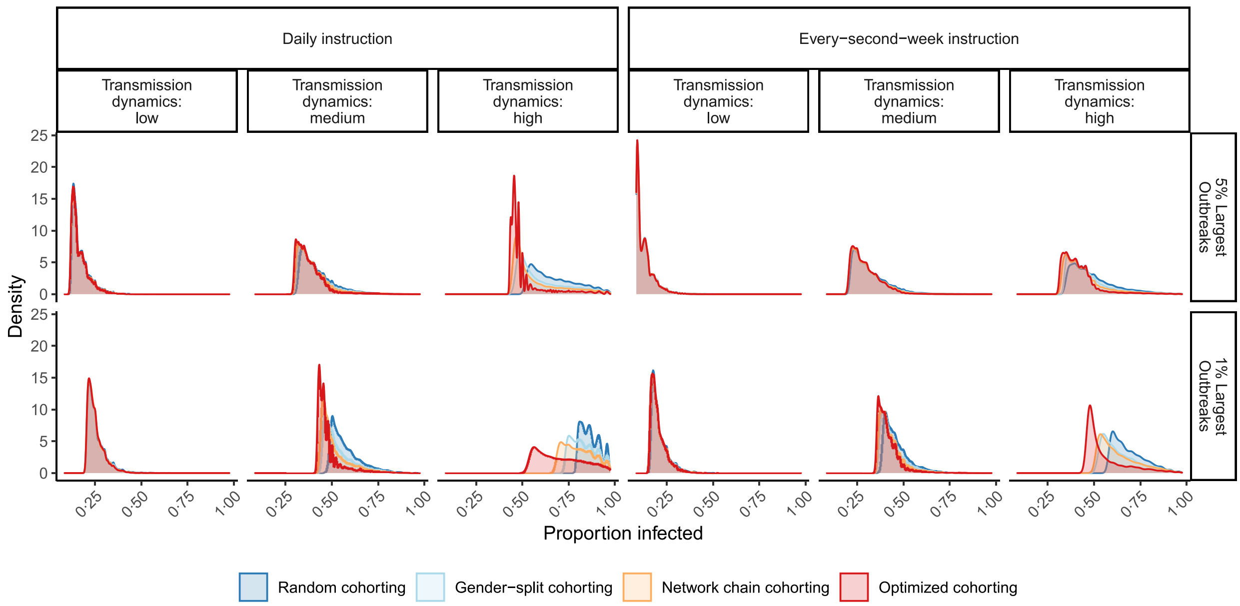

Fig. 6. Distribution of infections in the 5% and 1% largest outbreaks for different cohorting strategies.

trigger quarantines, onward transmission in the second cohort is not necessary; after all, a single clinical infection is sufficient to induce a quarantine.

Considering the proportion of students quarantined and infected jointly, cohorting is thus most important when transmission dynamics are high. For example, at same-day instruction and high transmission dynamics, random cohorting results in 16% of outbreaks spreading to the second cohort, gender-split cohorting results in 11%, network chain cohorting in 8%, and optimized cohorting in 4%. Depending on its specific implementation, network-based cohorting thus can lower the frequency of spread by 34%-75% relative to random cohorting. The excess proportion of quarantined students can be reduced from 13% (random cohorting) to 12% (gender-split), 11% (network chain cohorting) and 10% (optimized cohorting); i.e., by 10-21% relative to random cohorting. The average proportion of infections falls from 10·1% (random cohorting) to about 9·4% in gender-split, 9·1% in network chain, and 8·7% in optimized cohorting; i.e., by 7-14% relative to random cohorting. While these reductions may appear modest, it is important to bear in mind that, especially in a situation with high incidence of SARS-CoV-2, they apply to a large number of classrooms, so that the aggregate number of infections and quarantines prevented is high.

Finally, Fig. 6 shows that it is particularly super-spreading events in schools that network-based cohorting strategies can effectively prevent. For all cohorting strategies, Fig. 6 displays the distribution of the proportion of infected students for the 5% and 1% largest outbreaks observed in our simulations. In the case of both medium and high transmission dynamics, substantially fewer students are involved in the largest outbreaks if gender-split, network chain, or optimized cohorting is employed rather than random cohorting. Optimized cohorting, for example, rarely results in outbreaks that affect more than 50% of the students in class, i.e., a single cohort. By contrast, the largest outbreaks under random cohorting frequently affect a larger proportion of the classroom because outbreaks spread to and, subsequently, within the second cohort. Gender-split and network chain cohorting are in-between these extremes. An exception to this pattern are low transmission dynamics, under which differences between cohorting strategies remain negligible even for the largest outbreaks.

We report results for a number of sensitivity analyses in the Supplementary Material. This includes reductions in contact probabilities (section E), which capture both potential changes in overall contact frequencies since 2010-11 and reduced contacts under pandemic conditions. We find that differences in the cohorting strategies persist with daily contact probabilities as low as 5%, i.e., one weekly out-of-school interaction for the median student. We also find similar results when considering a lower infectiousness of sub-clinical infections (section D) and when assessing more or less frequent high-risk contact in the classroom (section F).

In addition, the Supplementary Material assesses whether the relative effectiveness of different cohorting strategies varies across individual classrooms, finding patterns identical to the aggregate results for almost all classrooms (section G). The only exception is the performance of gender-split relative to network chain cohorting: Network chain cohorting performs better in the majority of classrooms (as reflected in the aggregate results), but gender-split cohorting proves more effective in a minority of classrooms. This is unsurprising because gender-split cohorting can be particularly effective in those classes with even gender composition and strong gender segregation in out-of-school contacts. We also find that epidemiological outcomes are virtually indistinguishable between classrooms with predominantly native students and classrooms with a higher share of immigrant students (section H).

Finally, we investigate two variants of the model in the Supplementary Material. First, we consider a third mode of cohort instruction that was popular in the U.S. but less so in Europe (section I). In that mode, each cohort is instructed for two days of the week (e.g., the first cohort on Monday and Tuesday, and the second cohort on Wednesday and Thursday, with no in-person instruction on Friday). This mode of instruction proves slightly more effective in curbing infections than every-second-week instruction if transmission is low (because there is *less* in-person instruction overall). However, it is less effective if transmission is high because the cohorts' cool-down periods are shorter in this setup. Second, we consider an extended model that also incorporates teachers as additional channels of transmission between cohorts (section J). Results are very similar to our main analysis and we continue to find that network-based cohorting strategies are more effective than random cohorting.

4. Discussion

With continually high incidence of SARS-CoV-2, effective social distancing strategies are required to avoid transmission and larger outbreaks in schools. One such strategy is cohorting, the decomposition of larger clusters of students into smaller isolated units. Simulating the transmission of SARS-CoV-2 in classrooms and out-of-school contact networks of students in England, Germany, the Netherlands, and Sweden, we show that cohorting helps contain outbreaks, substantially reducing the number of infected students. It proves particularly effective when conducted in a rota-system with cohorts receiving in-person instruction only every second week, which induces a weeklong cool-down period for each cohort.

However, the success of cohorting, especially in preventing large outbreaks, depends on whether cohorts can be isolated not only *within* the school context, but also in terms of *out-of-school* interaction. Unlike random cohorting, network-based cohorting strategies such as gender-split cohorting, optimized cohorting, and network chain cohorting (see Table 1) exploit clusters in social networks to achieve a cleaner separation of cohorts. Our simulations show that network-based strategies outperform random cohorting by more frequently containing outbreaks to a single cohort. They also reduce the frequency of quarantines and the number of students infected, though the latter effects are weak when transmission dynamics are low. In this case, network-based strategies mainly limit quarantines, thus keeping students in school more. When transmission dynamics are higher, e.g., with more transmissible variants such as B.1.1.7, these strategies also notably reduce infections. In particular, they substantially decrease the size of the largest outbreaks by containing them to a single cohort and preventing superspreading in classrooms.

Optimized cohorting, which explicitly minimizes the number of cross-cohort out-of-school contacts, performs best in our simulations. However, since this strategy requires centralized knowledge of all students' out-of-school contacts with classmates, it might be difficult to implement in practice. Network chain cohorting offers a simple approximation that also performs better than random allocation, as does gender-split cohorting, which exploits the fact that adolescents' out-of-school contacts are mostly among students of the same gender.

Some network-based cohorting strategies may have undesired pedagogical consequences. For example, network chain cohorting may cause socially awkward situations because it partly lays bare the social fabric of the classroom. By design, however, this strategy protects isolated students from being publicly exposed in the classroom as an entire half of the classroom, rather than only the set of isolated students, is not allocated by nomination. Splitting classrooms by gender may induce undesired social dynamics, especially for those students who have to be allocated to the other-gender cohort because of gender imbalance in the classroom. Teachers, school administrators, and policy makers need to weigh these potential pedagogical drawbacks against the benefits of each strategy and make decisions accordingly.

One limitation of our study is that it considers school contacts in isolation, while students of course also have other social relations, and these relations, in particular with family members, are associated with higher transmission risks than in-school interaction [16]. Policy makers should be aware that the contribution of classroom cohorting in reducing community incidence depends on the role of schools in transmission overall, the extent of which remains hitherto uncertain [16,33].

Our model rests on a number of core assumptions, and changes in these assumptions could change the outcomes we observe. First, we assume that some classmates meet outside of school. While sensitivity analyses with considerable reductions in contact frequencies show that network-based cohorting strategies remain effective even when out-of-school contact is less frequent, we do not consider a complete halt of out-of-school contacts. Second, in our analysis, we are limited to social network data from 2010-2011, and interaction patterns among students may have changed in the last ten years, particularly with the advent of social media. However, if social media mostly resulted in a decrease (or increase) of in-person interaction among classmates, this is captured by the variation in contact frequencies we consider. We are not aware of empirical evidence suggesting more fundamental change in the structure of adolescents' social networks. Third, we have to make assumptions on a number of key model parameters, such as the (classroom) secondary attack rate and the share of asymptomatic infections. We choose parameters in accordance with estimates from the extant literature but, unfortunately, cannot yet validate these parameters by comparing the predictions from our simulation model with empirically observed school outbreaks. Such data is rare (e.g., Ismail et al. [34], Ehrhart et al. [35]) and, for our purposes, would have to be available at the classroom level, account for asymptomatic infections, and allow to differentiate between in-school onward transmission and other transmission channels.

In the absence of such validation, the exact effects of different cohorting strategies to curbing in-school transmission of SARS-CoV-2 is not fully clear yet. However, there also are a number of conditions that may lead us to *underestimate* the importance of network-based cohorting. In our model, symptomatic students are quickly tested and quarantined. If high local incidence of SARS-CoV-2 leads to delays in testing or quarantines, network-based cohorting is likely to become more important. Furthermore, more transmissible variants than the wildtype (such as B.1.1.7) are likely to amplify classroom transmission dynamics, which increases the importance of effective cohorting. Further evolution towards higher transmissibility may even lead to dynamics outside the range of outcomes observed in our models.

Contributors

A.K. conceived the study. D.K. and A.K. designed the model with L. L. providing input. D.K. designed the software and inference framework, implemented the model, and processed the data. All authors jointly wrote the manuscript, interpreted the results, and approved the final version for submission

Data availability

Data can be requested from https://doi.org/10.4232/cils4eu.5656.3.3.0

For data access to be granted, a data access agreement has to be signed and a short research proposal has to be submitted and approved. Data are available for academic research and teaching only.

We provide all analysis code, including a (simulated) example data set at https://github.com/DavidKretschmer/covid-cohorting-code.

Declaration of Interests

All authors declare no competing interest.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.lanepe.2021.100166.

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