communications medicine

A Nature Portfolio journal

Article

https://doi.org/10.1038/s43856-026-01543-4

Implications for distancing measures on in-person school and work attendance from Italian post-pandemic social contact data

Check for updates

Lorenzo Lucchini[1,8], Valentina Marziano[2,8], Filippo Trentini[3], Chiara Chiavenna[1,4], Elena D'Agnese[1,5,6], Vittoria Offeddu[1], Mattia Manica[2], Piero Poletti[2], Duilio Balsamo[1,4], Giorgio Guzzetta[2], Marco Ajelli[7,9], Alessia Melegaro[1,4,9] ✉ & Stefano Merler[2,9]

Abstract

Background The collection of updated post-COVID-19 data on social contacts is critical for future epidemiological assessment and evaluation of non-pharmaceutical interventions.
Methods We conducted two waves of an online survey in Italy (March 2022 and March 2023), collecting representative data on direct (verbal/physical) and indirect (indoor co-location) contacts. Using a generalised linear mixed model, we analysed social contact determinants and the impact of work-from-home and distance learning on reducing a pathogen's reproduction number (R). Additionally, we calibrated an age-structured model to the 2023–2024 influenza A epidemic in Italy to explore the impact of alternative in-person attendance scenarios on infection attack rates.
Results We find that in-person attendance significantly increases contacts: adults attending in person have 1.69 times (95%CI: 1.55-1.83) more contacts than those staying home, while children/adolescents 2.36 (95%CI: 1.96-2.84). Limiting in-person work alone marginally affects R, whereas combining work-from-home with distance learning (from primary school onwards) reduces R by up to 23.2% (95%CI: 13.7-30.1%), with minimal additional benefit from suspending early childcare. In the influenza A case study, seasonal infection attack rates range from 14.7% (95%PI: 12.8–16.5%) under full in-person attendance to <0.2% under the most restrictive scenario. Moderate interventions (suspension of tertiary education and work-from-home) reduce attack rates by up to one fourth among adults (15-64 years) and one sixth among older individuals.
Conclusions This study provides post-pandemic contact matrices for Italy, essential for modelling transmission of respiratory pathogens, and quantitative evidence on the epidemiological impact of targeted physical distancing measures, thereby supporting future policy design.

Plain language summary

Respiratory viruses spread through everyday contacts between people. Understanding how human interactions changed after the COVID-19 pandemic is important for preparing for future outbreaks. We conduct two online surveys in Italy in 2022 and 2023 to measure the number of social contacts across different age groups. We explore factors associated with higher numbers of contacts and find that people attending work or school in person report substantially more contacts than others. We estimate how combining work-from-home and distance learning could reduce the transmission potential of respiratory viruses, using seasonal influenza to illustrate the impact on a real-world epidemic. These findings provide updated estimates of social contacts and can support policymakers in planning targeted measures to limit transmission during future epidemics.

[1]DONDENA Centre for Research on Social Dynamics and Public Policy, Bocconi University, Milano, Italy. [2]Center for Health Emergencies, Bruno Kessler Foundation, Trento, Italy. [3]Department of Decision Science, Bocconi University, Milano, Italy. [4]BIDSA, Bocconi Institute for Data Science and Analytics, Bocconi University, Milano, Italy. [5]Department of Economics and Management, University of Pisa, Pisa, Italy. [6]Department of Statistics, Computer Science, Applications, University of Florence, Firenze, Italy. [7]Laboratory for Computational Epidemiology and Public Health, Department of Epidemiology and Biostatistics, Indiana University School of Public Health, Bloomington, IN, USA. [8]These authors contributed equally: Lorenzo Lucchini, Valentina Marziano. [9]These authors jointly supervised this work: Marco Ajelli, Alessia Melegaro, Stefano Merler. ✉e-mail: alessia.melegaro@unibocconi.it

Respiratory infectious diseases are spread in human populations through interactions associated with social contacts, occurring during the execution of everyday life activities. During severe health emergencies caused by respiratory infectious agents, such as pandemics, the limitation in the number of social contacts enacted through governmental mandates and recommendations (sometimes referred to as "physical distancing" measures) can be an effective means to interrupt the chains of transmission and rapidly curb the disease spread[1,2]. However, such measures may come at extensive economic and societal costs. Among the many measures aimed at reducing the transmissibility of SARS-CoV-2, school closures have been widely debated[3] amidst concerns about their negative short- and long-term impact on young individuals' education and psychological well-being[3–5]. In addition to this, the suspension of most economic activities during the lockdown enacted by many countries in the spring of 2020 has resulted in massive economic damage, disruption of supply chains, and job losses[6], exacerbating poverty and inequality. To properly weigh the costs and benefits of physical distancing measures, a crucial step is to quantify their impact on transmissibility. This difficult task is usually addressed through mathematical modelling, which largely relies on the availability of information on how many social contacts individuals experience across different socio-demographic stratifications, social settings and activities[7–12]. Although such information was available, to some extent, for most countries at the onset of the COVID-19 pandemic[13–15], the individuals' behavioural responses and imposed restrictions[16] made it somewhat outdated[17]. Several social contact studies were conducted in selected countries to assess changes in human mixing patterns throughout the course of the epidemics[7,8,18–20]. However, as COVID-19-related restrictions have progressively been lifted in most countries starting in 2022[16,21], comprehensive knowledge of post-pandemic contact patterns is still missing[19,22–25]. Here, we provide updated evidence on nationwide Italian contact data covering both direct social contacts and indoor co-location contacts after all mandates were lifted. Contact diaries were collected through internet-based surveys conducted in March 2022 and March 2023. Additionally, we combine the collected contact pattern data with data on educational demographics and age-specific in-person workforce participation to quantify the potential impact of targeted governmental restrictions in reducing the reproduction number (R) of a novel respiratory pathogen. Finally, we calibrated an age-structured SEIR model to the 2023–2024 seasonal influenza A epidemic in Italy to evaluate the impact of in-person school and work attendance scenarios in a realistic epidemic context.

Methods

Data and data cleaning

We conducted a two-waves online social contact survey on a sample representative of the age (based on 10-year age groups up to a single 70+ group), sex, and area of residence (NUTS1 level, i.e. major socio-economic regions[26]) of the Italian population. The first wave covered the period from March 17 to March 29, 2022, and the second from March 17 to April 5, 2023. Except for minor updates (e.g., for the number of vaccine doses recommended to the population in 2023), the second wave was identical to the first and administered to a random group of respondents who already participated in the first wave (1246 participants), and to a group of first-time respondents of approximately equal size. The survey was administered to both adults (18 or more years old) and minors (less than 18 years old). Participants aged 14 to 17 years were requested to compile the questionnaire under the supervision of legal guardian (usually a parent); for participants under 14, the compilation was performed by a legal guardian, and the active engagement of the mnior participant was strongly encouraged to ensure accurate responses to the questions.

The survey consists of two main sections: i) socio-demographics, health-related information and behavioural information on the respondent, and ii) a contact diary in which respondents were asked to recall their "direct" and "indirect" contacts on the day prior to the survey administration. A direct contact was defined as a person with whom physical interactions (e.g., a handshake, a pat on the back, a hug, a kiss, etc.) and/or in-person verbal exchanges of at least five words occurred. Participants were asked to provide details on each of their direct contacts, such as their age, sex, or the setting in which the interaction occurred. No information about the duration of these contacts was requested. An indirect contact was defined as a person with whom the respondent was co-located in a closed environment for at least 30 minutes (e.g., classmates at school or colleagues at work). This definition was specifically designed to make respondents report only transmission-relevant contacts. For the main analysis in this study, we defined a contact as any direct or indirect contact. After data collection, responses underwent an accurate data-cleaning process including: i) removal of respondents with inconsistencies in responses, and ii) removal of respondents with incomplete information. A complete description of the data-cleaning procedure is provided in Supplementary Information, section 1.1. After data cleaning, the collected responses maintained a sample representativeness within a population-to-sample ratio below 2 for all targeted demographic groups (see Supplementary Figs. 2 and 3). Full details on the collected information, the methodology, and data representativeness are reported in the Supplementary Information.

Indirect co-location events augmentation procedure

For each direct contact, additional information was collected about the characteristics of the interaction and information on the contacts themselves. However, indirect contacts were only reported as an aggregate number. To include indirect contact data in the analysis of contact patterns it was thus necessary to augment them with the relevant missing information.

The data augmentation procedure used in the baseline analysis can be summarized as follows. For each respondent:

i) we defined the number of indirect contacts to be augmented (N), by subtracting from the reported count for indirect contacts the number of indoor direct contacts that they reported. This assumption conservatively accounts for contacts potentially reported both as direct indoor and as indirect.
ii) we reconstructed the age and setting of indirect contacts by sampling N times (with replacement) this information from the set of direct contacts reported by the same participant, excluding cohabitants and outdoor contacts.
iii) if the respondent did not report direct contacts, indirect contacts data augmentation was performed by sampling the information from direct contacts of other participants of the same age as the respondent.

We performed a sensitivity analysis on the data augmentation procedure by limiting the sampling for the assignment of indoor contacts only to the setting in which the respondent reported most of their direct contacts, rather than sampling from the overall direct contacts. See Supplementary Information, section 1.2 for more details.

Determinants of social contacts: the statistical framework

To investigate the determinants of the total number of contacts, we fitted a generalised linear mixed model (GLMM)[27]. We modelled the total number of contacts as a function of the covariates measured in the survey using GLMM with negative binomial distribution and log-link function (see Supplementary Information, section 1.3). We initially screened 35 covariates relative to the respondent and cohabitant's characteristics for significant associations with the total number of contacts, fitting a set of negative binomial regression models. We built these models using as independent variables each individual covariate, an intercept, and a term accounting for the different data collection waves (2022 or 2023). Covariates that were not significant in the multivariate model were subsequently filtered out. These included, among others, the NUTS1-level region of residence, presence in the household of cohabitants of specific age-groups (children excluded), and whether the respondent knew someone who was hospitalized or died due to COVID-19 (see Supplementary Table 6 for a full list of the screened covariates). The final model included 14 covariates: age group aggregated by 10-year intervals, occupation, household income,

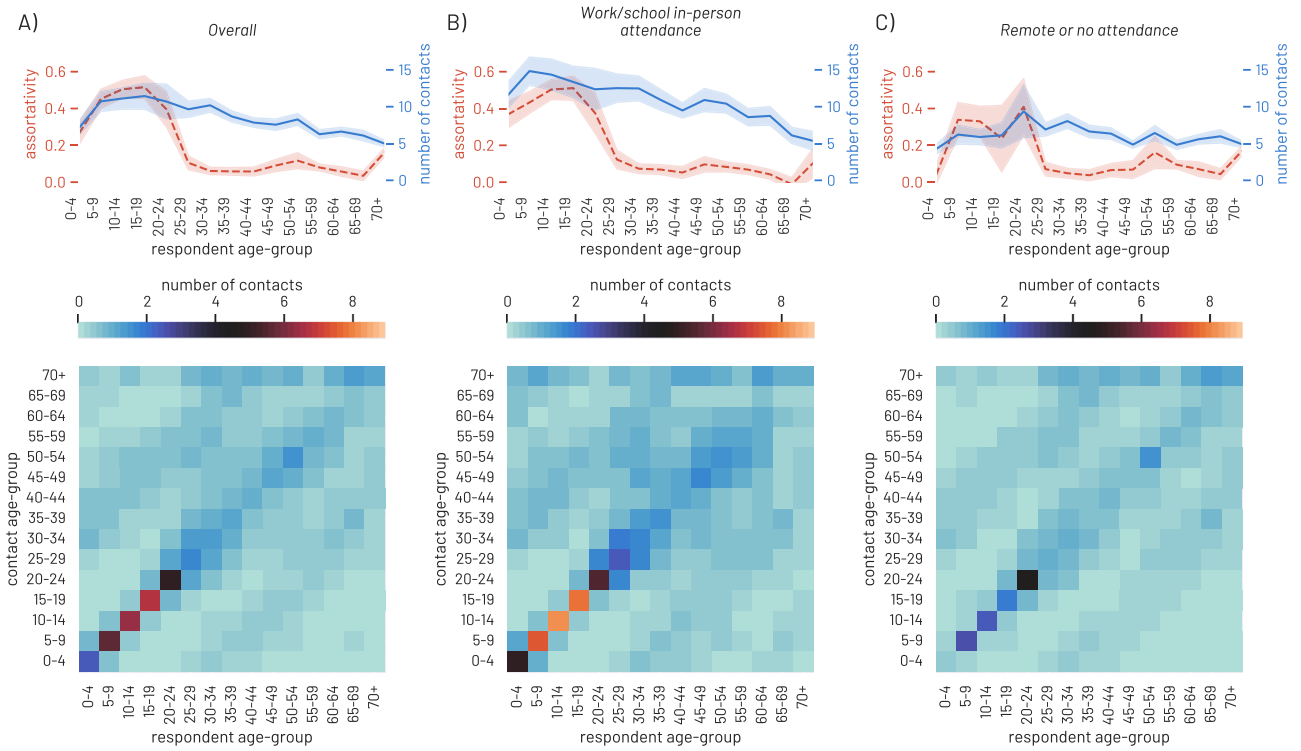


Fig. 1 | Age-specific contact patterns based on survey data from both waves (March 2022 and 2023). Matrices were constructed by averaging 1,000 bootstrap samples with replacement of survey responses. Each cell represents the mean number of total contacts per individual, stratified by age group pairs. The top panels indicate the mean number of contacts (full line) and the mean age assortativity[8,52] (dashed line) for each age group. Shaded areas report the 95%CI of the number (blue) and assortativity (red) of social contacts by age, computed from the $n = 1{,}000$ bootstrap-resampled contact matrices. **A** Contact patterns obtained from the full sample, representative of the Italian population. **B** Contact patterns for the subset of individuals attending school or work in person. **C** Contact patterns for the subset of individuals not attending schools or working in person.

household size, in-presence attendance at work/school, contact happened on a Sunday, completion of SARS-CoV-2 primary vaccination cycle, recent (in the last 4 months) SARS-CoV-2 infection, presence of chronic comorbidities in the respondent, presence of chronic comorbidities in cohabitants, senior (65 years or older) cohabitants, having children, and participation to the first survey wave. Finally, a random intercept accounted for the within-individual correlation in longitudinal responses across the two waves. Full details on the generalised linear mixed model selection are reported in Supplementary Information, section 1.3.

Age-specific contact matrices

We constructed age-specific matrices of average total contacts for the Italian population stratified by 15 age groups (0–4, 5–9, 10–14, 15–19, 20–24, 25–29, 30–34, 35–39, 40–44, 45–49, 50–54, 55–59, 60–64, 65–69, and 70+ years old). We then computed the population normalised reciprocal contact matrix, following established procedures from the literature[8,13,23]. The matrices for the average total contacts obtained by 1000-fold bootstrapping of responses from both waves are reported in Fig. 1 (see also Supplementary Fig. 12 for robustness). We also constructed contact matrices disaggregated by attendance to work/school: in-person or remote/no-attendance (Fig. 1). In the SI, we report contact matrices disaggregated by setting (Supplementary Figs. 6–8) and matrices including only direct social contacts (Supplementary Fig. 10).

Effect of school and work attendance on the transmissibility of a generic respiratory virus

Throughout the manuscript, we consider the reproduction number as a measure of a pathogen's transmissibility. We evaluated the potential effect of different scenarios of school and work attendance on the reproduction number of a novel respiratory virus (i.e., spreading in a fully susceptible population in the absence of interventions) under the assumption of homogeneous susceptibility and infectiousness across age groups. To do so, we combined data from Eurostat on age-specific populations attending different education levels[28] (from early childhood to tertiary education) and on age-specific in-person workforce in Italy from a previously published study[11].

These data were used to define scenarios combining various levels of in-person work and school attendance, assuming that these two dimensions could vary independently. The considered scenarios reflect the progressive physical closure of education levels, starting from tertiary education (ISCED 5-8) and progressively including lower levels, combined with three levels of in-person attendance at work: i) "pre-pandemic", corresponding to data before 2020; ii) "sustainable", reflecting the proportion of in-person workers observed in Italy after the reopening of economic activities following the COVID-19 lockdown on May 18, 2020; and iii) "minimum", where only essential workers are allowed to work in person, as during the 2020 national lockdown. The age-specific populations of students enrolled in the different education levels are reported in Fig. 2A, and those of in-person workers in the three scenarios are reported in Fig. 2B. For each scenario, we quantify the relative change in reproduction numbers compared to a baseline scenario with full in-person attendance. Specifically, we denote by R_s the reproduction number associated with scenario s and compute the relative reduction α_s with respect to the baseline scenario with full school and work attendance:

$$\alpha_s = 1 - \frac{R_s}{R_0} = 1 - \frac{\rho(NGM_s)}{\rho(NGM_0)} \quad (1)$$

where $\rho(NGM_s)$ and $\rho(NGM_0)$ represent the dominant eigenvalues of the Next-Generation Matrices associated with scenario s and with the baseline scenario, respectively[11,29,30].

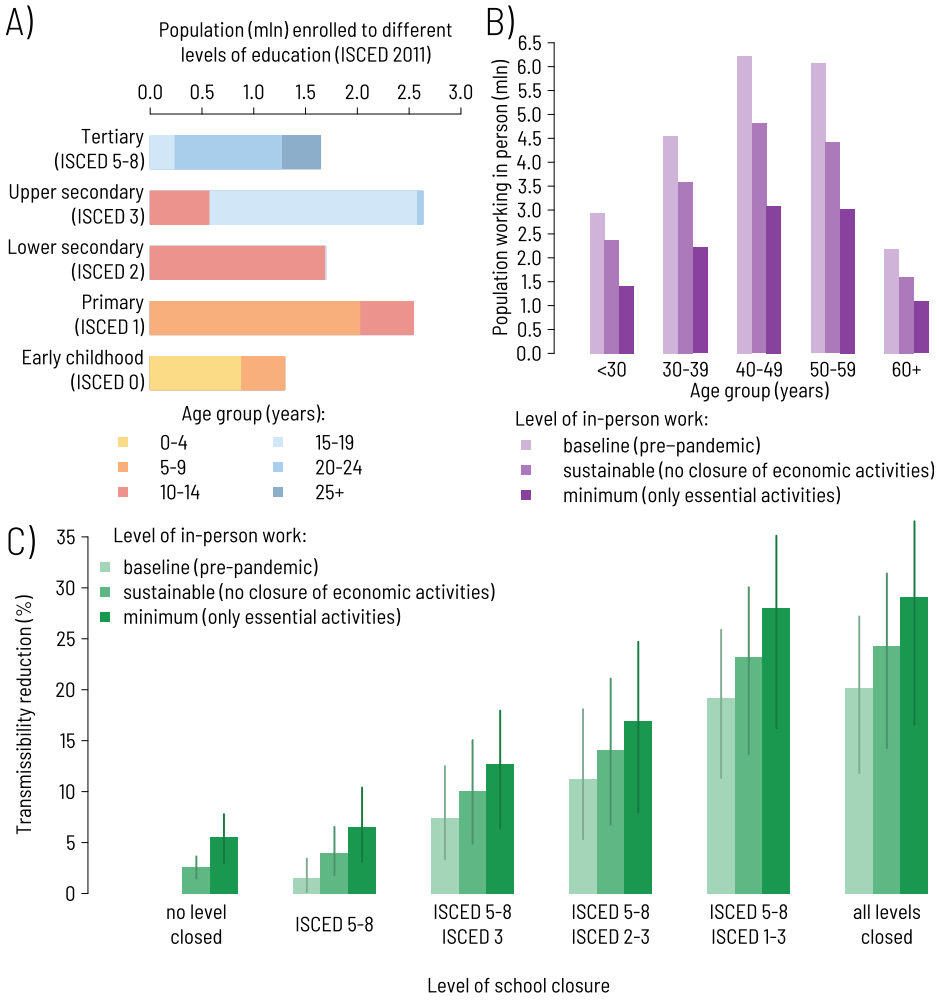


Fig. 2 | Transmissibility reduction under different scenarios of work/school attendance. A Age-specific population enrolled to different educational levels in Italy in 2020, according to the ISCED classification 2011[28]. **B** Age-specific population working in person in Italy under the three considered scenarios[11]: baseline (corresponding to pre-pandemic estimates); sustainable (corresponding to the population after the reopening of all economic activities following the end of the COVID-19 lockdown in May 2020); minimum (corresponding to in-person workers estimated during the COVID-19 lockdown). **C** Relative reduction in transmissibility associated with intervention scenarios combining different levels of school closures (including distance-learning mandates) and in-person work, compared to a baseline scenario where the in-person workers are set at pre-pandemic levels[11] and students across all education levels attend in person. Bars show mean estimates across $n = 1000$ bootstrap-resampled contact matrices; error bars indicate the corresponding 95%CI.

Since infection-related parameters are the same across scenarios, α_s can be simplified to:

$$\alpha_s = 1 - \frac{\rho(M_s)}{\rho(M_0)} \tag{2}$$

where M_s is a block-matrix

$$M_s = \begin{pmatrix} A^s_{i,j} & A^s_{i,j} \\ B^s_{i,j} & B^s_{i,j} \end{pmatrix} \tag{3}$$

The blocks are defined as

$$A^s_{i,j} = C^P_{i,j} \frac{N^P_i(s)}{N^P_j(s) + N^{NP}_j(s)} \tag{4}$$

and

$$B^s_{i,j} = C^{NP}_{i,j} \frac{N^{NP}_i(s)}{N^P_j(s) + N^{NP}_j(s)} \tag{5}$$

with

- $C^P_{i,j}$ representing the overall contact matrix estimated for the population attending work or school in-person;
- $C^{NP}_{i,j}$ representing the overall contact matrix estimated for the population not attending work or school in-person;
- $N^P_i(s)$ representing the number of individuals of age i attending schools or work in-person in scenario s;
- $N^{NP}_i(s)$ representing the number of individuals of age i not attending schools or work in-person in scenario s.

We performed two additional sensitivity analyses considering heterogeneous susceptibility across age groups, as estimated for the 2009 H1N1 pandemic virus and for SARS-CoV-2 ancestral lineages (see Supplementary Information, section 2.5)[31,32]. Details on the computation on the Next-Generation Matrix for the main and sensitivity analyses are reported in the Supplementary Information, section 1.5.

An application to seasonal influenza in Italy, 2023–2024

We developed a deterministic SEIR model to simulate the 2023–2024 seasonal influenza A epidemic in Italy. The model population, representing the Italian population of approximately 59 million individuals, was stratified by age and into two subgroups (attending schools/workplaces "in-person" or "not-in-person"), with mixing patterns informed by the mean contact matrices estimated in this study.

The latent period was set to 1.5 days and the infectious period to 1.2 days in such a way that the resulting generation time is 2.7 days, in agreement with the literature[33]. The model accounts for age-specific susceptibility to infection based on estimates from past influenza A seasons[33]. Model calibration was performed against the weekly incidence of influenza A (weeks 46/2023–17/2024) estimated by the Influcast project[34] using a Metropolis–Hastings MCMC algorithm with a negative binomial likelihood to account for overdispersion. The model includes four free parameters: the scaling factor for transmissibility, the reporting ratio, the number of

infectious individuals at the start of the simulations, and the overdispersion parameter of the negative binomial distribution, which we use to compute the likelihood of observing the weekly incidence given the simulated one. Calibration was conducted under the assumption of full in-person attendance, and posterior parameter distributions (Supplementary Fig. 4) were used to simulate alternative attendance scenarios. Model outcomes under different scenarios were compared in terms of both overall and age-specific infection attack rates at the end of the simulation period (week 17/2024). Further details on the model are reported in Supplementary Information section 1.6.

Ethics statement

This study was conducted in accordance with the ethical standards set by Bocconi University and has received approval from the Bocconi University Ethical Board (Approval Number: FA000383 − 17 January 2022). Participants were informed about the nature and purpose of the research, including the voluntary nature of their participation and their right to withdraw at any time without any negative consequences. Upon completion, participants received compensation for their time and effort through the survey company. Informed consent was obtained from all participants prior to their involvement in the study. All analyses were carried out on anonymised data.

Results

This contact survey data collection, after screening and cleaning, included 3743 participants producing 4979 valid questionnaires, of which 2474 were from the 2022 wave and 2505 from the 2023 wave. A subset of 1236 participants responded to both the 2022 and 2023 waves. Summary descriptions of the participants' characteristics and the corresponding mean numbers of contacts are reported in Table 1 and Table 2. Full details on the collected information are reported in the Supplementary Information.

The sample across the two waves included 124 children of preschool age (0-5 years), 66.1% of whom were enrolled in early childhood education services (ISCED level 0[28]), and 317 individuals aged between 6 and 17 years, all of whom were enrolled in primary and secondary education (ISCED levels between 1 and 3). Among participants aged 18 or older (3,309, representing 88.4% of respondents), 51.6% were employed either full-time or part-time, 8.6% were looking after the home or family, 3.8% were students (full-time or part-time), 26.3% were retired, and 9.7% were inactive.

A total of 37,584 contacts were reported in the two study waves, of which 23,718 (63%) were direct and 13,866 (37%) were indirect (see Supplementary Tables 7, 8, and 9 for a detailed breakdown of direct and indirect contacts). Overall, 95.3% of the responses reported at least one contact on the previous day. Most of the contacts (90.8%) were reported in indoor settings, primarily at home (54.9% of total contacts). Contacts at school or work accounted for 9.7% of reported contacts, leisure social contacts for 18.8%, contacts on transportation means for 2.5%, and 14.2% of contacts were reported in other non-specified settings (see Supplementary Table 9).

The mean number of reported daily contacts per respondent across the two waves was 7.5 (95% bootstrapped Confidence Interval (CI) of the mean: 7.2–7.9) and was highly heterogeneous by age group, educational attainment, and household size (Table 1). Significant differences were found with respect to employment status and attendance at work/school (Table 2). Among adult respondents who were employed, those who worked in person reported a higher number of social contacts, 9.4 (95%CI: 8.7–10.1), compared to those who worked remotely or did not work, 5.2 (95%CI: 4.6–6.0). Attendance to work was similar across the two waves (25.1% of the sample reported working remotely or not working in the 2022 wave and 26.5% in the 2023 wave). Similarly, students attending schools and universities in person reported a higher number of contacts, 16.2 (95%CI: 14.8–17.6), compared to those who did distance learning or did not attend school at all, 8.2 (95%CI: 6.2–10.5). During the 2022 wave, 55.6% of students attended school or university in person, compared to 69.9% among students from the 2023 wave. Overall, this study shows a higher number of reported contacts with respect to the CoMix study[35], which estimated for Italy an average number of contacts of 3.6 (95%CI: 3.3–3.9) during February-April 2021. However, it also reveals a substantially lower number of reported contacts with respect to POLYMOD data[13], which estimated for Italy an average number of contacts of 19.8 (95%CI: 19.0–20.6). In this case, data were collected through paper surveys during April 2006 (see Supplementary Table 4 for a more detailed comparison).

Determinants of social contacts

Two separate GLMMs with negative binomial distribution were fitted to data from adults and minors to account for the different available covariates (see Supplementary Information, section 2.1). Among adults, the main factors contributing to a higher number of contacts were in-person attendance to work or school, living in larger households, younger age, and having completed the primary cycle (i.e., at least two doses) of the COVID-19 vaccine (Fig. 3). Adults who attended school or work in person reported 1.69 (95%CI: 1.55–1.83) times the contacts of those who attended remotely or did not attend. Adults who lived in households of size 4 reported 1.51 (95%CI: 1.32–1.71) times the contacts of individuals living alone. Individuals of age 40 or more reported significantly fewer contacts than individuals in the age group 18–29, with a contact rate ratio ranging, on average, between 0.70 (95%CI: 0.61–0.82) in the age group 40–49 and 0.81 (95%CI: 0.69–0.95) in the age group 60–69. Respondents who received at least two COVID-19 vaccine doses reported 1.26 (95%CI: 1.11–1.42) times the contacts of unvaccinated or incompletely vaccinated respondents. Weaker but significant effects were estimated for educational attainment, income levels, and the presence of a cohabitant with underlying conditions. When comparing responses across waves, we find a small but significant increase in the number of reported contacts, with the second wave showing 1.12 (95% CI: 1.06-1.17) times more contacts than the first wave (see also Supplementary Tables 7-10 for a more detailed breakdown of the number of contacts by wave). Consistent with results for the adult population, in-person attendance at school was the most important determinant of the number of contacts, also among minors, with in-person attendees reporting 2.36 (95%CI: 1.96–2.84) times the contacts of students not attending (see Supplementary Fig. 5).

We ran a sensitivity analysis where we considered, for both minors and adults, only direct contacts as an alternative outcome variable. Results show that in-person school/work attendance was the most important determinant of the number of contacts, also in this case (see Supplementary Information, section 2.3).

Effect of in-person school and work attendance on viral transmissibility

Based on data collected across the two waves, we estimated a contact matrix by age, representing the mean number of daily contacts that an individual of age i has with individuals of age j (Fig. 1A). Contact matrices were also estimated, stratifying into respondents who attended school or worked in person (Fig. 1B) and by those who did not (Fig. 1C). Individuals who attended school or work in person are characterised by an overall higher number of interactions across all age groups, and by a higher level of assortative mixing in younger age groups, i.e., the tendency to interact with groups of similar age (top panels in Fig. 1). These matrices were used to assess the impact of work-from-home and distance learning in reducing the reproduction number of a generic respiratory virus.

Using measures targeting only work attendance, we estimated a maximum reduction in transmissibility of 5.5% (95%CI: 3.0-7.8%) compared to the baseline scenario (Fig. 2C) when only essential workers are allowed to attend in person. A transmissibility reduction of about 2.6% would result from a "sustainable" scenario where only limited work-from-home mandates are put in place on non-essential workers[11]. Adding to this scenario the progressive suspension of in-person education services would result in transmissibility reductions of: 4.0% (95%CI: 1.8–6.5%) when tertiary education alone is suspended, (ISCED 5–8); 10.0% (95%CI: 4.9–15.1%) when including the upper secondary (ISCED

Table 1 | Survey respondents' characteristics and average contacts by wave

Variables	March 2022 wave		March 2023 wave		Both waves	
	Sample size	Avg. Contacts (95% CI)	Sample size	Avg. Contacts (95% CI)	Sample size	Avg. Contacts (95% CI)
Total	2474	7.3 (6.9–7.7)	2505	7.8 (7.3–8.2)	4979	7.5 (7.2–7.9)
Age group						
0–9	150 (6.1%)	11.1 (9.5–12.7)	106 (4.2%)	12.6 (10.4–14.9)	256 (5.1%)	11.7 (10.4–13)
10–19	165 (6.7%)	12.7 (10.9–14.6)	107 (4.3%)	14.9 (12.4–17.7)	272 (5.5%)	13.6 (12.1–15.2)
20–29	202 (8.2%)	10.4 (8.5–12.6)	173 (6.9%)	11 (8.9–13.4)	375 (7.5%)	10.7 (9.3–12.3)
30–39	376 (15.2%)	8 (6.9–9.2)	341 (13.6%)	8.8 (7.7–10.1)	717 (14.4%)	8.4 (7.6–9.3)
40–49	381 (15.4%)	6 (5.1–7.1)	353 (14.1%)	6.7 (5.8–7.6)	734 (14.7%)	6.4 (5.7–7.1)
50–59	432 (17.5%)	6.3 (5.4–7.2)	484 (19.3%)	7.6 (6.6–8.7)	916 (18.4%)	7 (6.3–7.7)
60–69	320 (12.9%)	6.5 (5.4–7.7)	382 (15.2%)	6.3 (5.4–7.4)	702 (14.1%)	6.4 (5.7–7.2)
70 +	448 (18.1%)	4.8 (4.2–5.5)	559 (22.3%)	5.7 (5–6.5)	1007 (20.2%)	5.3 (4.8–5.8)
Sex						
Male	1248 (50.4%)	7.5 (6.9–8.1)	1272 (50.8%)	8.2 (7.6–8.9)	2520 (50.6%)	1248 (50.4%)
Female	1226 (49.6%)	7.1 (6.6–7.7)	1233 (49.2%)	7.3 (6.8–7.9)	2459 (49.4%)	1226 (49.6%)
Net household income (euros per month)						
< 1,500	583 (23.6%)	5.8 (5.1–6.7)	568 (22.7%)	6.3 (5.5–7.2)	1151 (23.1%)	6.1 (5.5–6.7)
1,500–2,999	967 (39.1%)	7.5 (6.8–8.2)	1002 (40%)	7.6 (7–8.2)	1969 (39.5%)	7.5 (7.1–8)
> 3,000	509 (20.6%)	8.9 (8–10)	551 (22%)	10.2 (9.1–11.5)	1060 (21.3%)	9.6 (8.8–10.4)
Undisclosed	415 (16.8%)	7.1 (6.2–8.2)	384 (15.3%)	6.8 (5.8–7.8)	799 (16%)	7 (6.3–7.7)
Household size						
1	357 (14.4%)	5.2 (4.5–6)	355 (14.2%)	5.9 (4.9–6.9)	712 (14.3%)	5.5 (4.9–6.2)
2	745 (30.1%)	5.7 (5–6.5)	844 (33.7%)	6.5 (5.7–7.2)	1589 (31.9%)	6.1 (5.6–6.6)
3	732 (29.6%)	8.2 (7.3–9.1)	677 (27%)	8.5 (7.6–9.3)	1409 (28.3%)	8.3 (7.7–8.9)
4	502 (20.3%)	9.1 (8.2–10.1)	492 (19.6%)	9.6 (8.7–10.6)	994 (20%)	9.3 (8.7–10.1)
5+	138 (5.6%)	10.5 (8.7–12.6)	137 (5.5%)	11.1 (9.3–13.1)	275 (5.5%)	10.8 (9.4–12.2)
NUTS1 regions						
North-West	683 (27.6%)	8.3 (7.4–9.3)	691 (27.6%)	7.6 (6.8–8.5)	1374 (27.6%)	8 (7.3–8.6)
North-East	473 (19.1%)	7.5 (6.7–8.5)	492 (19.6%)	8 (7.1–9)	965 (19.4%)	7.8 (7.1–8.5)
Centre	500 (20.2%)	6.5 (5.9–7.2)	492 (19.6%)	8.3 (7.4–9.4)	992 (19.9%)	7.4 (6.8–8)
South	561 (22.7%)	7 (6.1–7.9)	569 (22.7%)	7.6 (6.8–8.6)	1130 (22.7%)	7.3 (6.7–8)
Islands	257 (10.4%)	6.7 (5.5–8.1)	261 (10.4%)	7 (5.7–8.5)	518 (10.4%)	6.8 (5.9–7.8)
COVID-19 vaccination status						
None	218 (8.8%)	6.8 (5.7–8.1)	212 (8.5%)	6.4 (5.3–7.6)	430 (8.6%)	6.6 (5.8–7.5)
1 dose	23 (0.9%)	7.2 (4.6–10.4)	28 (1.1%)	7.9 (5.1–11)	51 (1%)	7.6 (5.6–9.7)
2 doses	290 (11.7%)	8.7 (7.4–10.2)	310 (12.4%)	8.6 (7.4–10)	600 (12.1%)	8.7 (7.7–9.7)
3+ doses	1839 (74.3%)	7 (6.6–7.6)	1880 (75%)	7.6 (7.1–8.1)	3719 (74.7%)	7.3 (7–7.7)
Exempt	104 (4.2%)	9.3 (7.6–11.2)	75 (3%)	13 (9.8–16.7)	179 (3.6%)	10.9 (9.2–12.8)

The table reports the number of respondents (and the percentage with respect to the number of respondents in each wave) and respondents' average number of social contacts (and 95% Confidence Intervals (CI)) stratified by different respondent characteristics: age, sex, household income, household size, NUTS1 region, and COVID-19 vaccination status. Average and CI are computed through 10,000 bootstrap iterations, sampling with replacement from the set of respondents within each demographic group.

3); 14.1% (95%CI: 6.7–21.1%) with lower secondary (ISCED 2); 23.2% (95%CI: 13.7–30.1%) with primary education (ISCED 1); and 24.2% (95%CI:14.2-31.4%) with early childhood education (ISCED 0). The maximum transmissibility reduction, achievable by also limiting attendance in-person to only essential workers in addition to suspending all in-person schooling, was estimated to be 29.1% (95%CI: 16.6–36.5%) (see Fig. 2C for detailed results on transmissibility reduction).

To assess the robustness of our results to alternative assumptions on age-specific susceptibility, we conducted two sensitivity analyses using susceptibility estimates from the 2009 H1N1 pandemic virus and from SARS-CoV-2 ancestral lineages[31,32]. Under the H1N1 estimates, where susceptibility is higher in children compared to adults and the elderly, interventions targeting work attendance alone were markedly less effective in reducing the transmissibility than in the main analysis, which assumed homogeneous susceptibility across ages (see Supplementary Fig. 14A). We estimated that limiting in-person work to essential workers reduced the reproduction number by 0.33% (95%CI: 0.16–0.56%), compared with 5.5% (95%CI: 3.0–7.8%) in the main analysis. In contrast, combining full school closure with the maximum level of work restrictions resulted in an average reduction of 62.0% (95%CI: 52.1–69.8%), nearly twice the effect obtained in the main analysis (29.1%). By contrast, when adopting the SARS-CoV-2 estimates, where susceptibility is higher in the elderly compared to adults and children, interventions targeting work attendance were estimated to be more effective than in the main analysis (see Supplementary Fig. 14B). Without school closure, restricting in-person work to essential workers yielded an 8.8% transmissibility reduction (95%CI: 6.5–10.8%), slightly

Table 2 | Survey respondents' sample and average contacts by wave

Variables	March 2022 wave		March 2023 wave		Both waves	
	Sample size	Avg. Contacts (95% CI)	Sample size	Avg. Contacts (95% CI)	Sample size	Avg. Contacts (95% CI)
Educational attainment						
Lower secondary or below	324 (13.1%)	6.5 (5.4–7.6)	329 (13.1%)	6.5 (5.4–7.6)	653 (13.1%)	6.5 (5.7–7.2)
Upper secondary	1380 (55.8%)	6.8 (6.3–7.4)	1377 (55%)	7.3 (6.8–7.8)	2757 (55.4%)	7.1 (6.7–7.4)
Tertiary or above	770 (31.1%)	8.5 (7.8–9.4)	799 (31.9%)	9.2 (8.3–10.1)	1569 (31.5%)	8.9 (8.3–9.5)
Employment status						
Employed (full or part-time)	1103 (44.6%)	7.6 (7–8.3)	1199 (47.9%)	8.5 (7.9–9.3)	2302 (46.2%)	8.1 (7.6–8.6)
Looking after home/ family	179 (7.2%)	4 (3.4–4.6)	204 (8.1%)	5.8 (4.9–7)	383 (7.7%)	5 (4.4–5.6)
Student (full- or part-time)	378 (15.3%)	12.6 (11.3–13.9)	253 (10.1%)	14 (12.3–15.8)	631 (12.7%)	13.1 (12.1–14.2)
Retired	272 (11%)	5.6 (4.4–7.1)	216 (8.6%)	4.9 (4.1–5.8)	488 (9.8%)	5.3 (4.5–6.2)
Inactive	542 (21.9%)	5 (4.3–5.8)	633 (25.3%)	5.4 (4.8–6.1)	1175 (23.6%)	5.2 (4.8–5.7)
Working mode (only employed respondents during weekdays)						
Remote or did not attend	195 (25.1%)	4.9 (4.1–5.7)	218 (26.5%)	5.6 (4.6–6.8)	413 (25.8%)	5.2 (4.6–6)
In-person	582 (74.9%)	8.5 (7.7–9.4)	604 (73.5%)	10.2 (9.2–11.3)	1186 (74.2%)	9.4 (8.7–10.1)
School attendance (only student respondents during weekdays)						
Remote or did not attend	72 (26.4%)	8.4 (5.9–11.3)	29 (13.9%)	7.8 (5.2–11)	101 (21%)	8.2 (6.2–10.5)
In-person	201 (73.6%)	15.7 (14.1–17.4)	179 (86.1%)	16.8 (14.6–19.1)	380 (79%)	16.2 (14.8–17.6)

The table reports the number of respondents included in the survey (and their population percentage with respect to the number of respondents per wave) and respondents' average number of social contacts (and 95% confidence intervals) stratified by additional respondent characteristics: educational attainment, employment status, working mode (e.g., remotely or in-presence), school attendance (e.g., distance or in-presence learning). Average and Confidence Intervals (CI) are computed through 10,000 bootstrap iterations sampling with replacement from the set of respondents within each variable group.

higher than in the main analysis. Conversely, the maximum combined effect of full school closure and work restrictions was weaker, resulting in a 20.3% reduction (95%CI: 9.5–27.9%), compared with 29.1% in the main analysis.

An application to seasonal influenza in Italy, 2023–2024

We calibrated an age-structured SEIR model to the 2023–2024 epidemic of seasonal influenza A in Italy and used it to project the impact of alternative school and workplace attendance scenarios on infection attack rates at the end of the season (Fig. 4). The model was calibrated to weekly influenza A incidence, assuming full-in person work and school attendance (Fig. 4A). Overall infection attack rates varied substantially across the scenarios considered, ranging from 14.7% (95% Prediction Intervals, PI: 12.8–16.5%) under full in-person attendance to less than 0.2% when all education levels were suspended and in-person work was restricted to its minimum level (Fig. 4B).

In the scenario of full in-person attendance, we estimated infection attack rates of 33.7% (95%PI: 30.2–36.9%) among individuals aged 0–14 years, 10.0% (95%PI: 8.6–11.4%) among those aged 15–64 years, and 17.0% (95%PI: 14.6–19.2%) among adults aged 65 years and older.

Considering moderate intervention scenarios, suspending in-person tertiary education alone had a limited effect on infection attack rates across all age groups compared with the full in-person attendance scenario. Specifically, infection attack rates were estimated to decrease to 33.0% (95%PI: 29.5–36.2%) in 0-14 years, to 9.4% (95%PI: 8.0–10.6%) among those aged 15-64 years, and to 16.3% (95%PI: 14.0–18.4%) in those aged 65 years and older (Fig. 4C). Combining the suspension of in-person tertiary education with a "sustainable work" limitation led to stronger reductions, particularly in the 15–64-year age group, which includes the majority of workers, where infection attack rates decreased to 7.5% (95%PI: 6.4–8.6%).

When exploring more stringent scenarios, infection attack rates decreased to 12.4% (95%PI: 10.5–14.1%) in the ≥ 65-year age group when in-person work was kept at its minimum without school closures, and to 11.9% (95%PI: 10.2–13.6%) when in-person tertiary education was also suspended. Comparable reductions among school-aged children (0–14 years) could instead be achieved only by suspending in-person attendance from upper secondary education upward, combined with at least a "sustainable" reduction in workplace attendance. Finally, combined interventions involving school closures from the primary level upward resulted in infection attack rates reduced by two-thirds in all age groups compared to the full-attendance scenario, regardless of the level of in-person work considered (Fig. 4C).

Discussion

In this study, we analysed data from a social contact survey conducted in Italy in two waves. The first wave took place in March 2022, immediately after the surge and decline of the Omicron variant[36,37]. The second wave was conducted in March 2023, several months after all restrictions had been lifted[38] and a month before the declaration of the end of the COVID-19 Public Health Emergency of International Concern[39]. Respondents in the second wave reported a slight but statistically significant increase in the number of social contacts compared to the first wave, which may be attributed to the relaxation of the remaining restrictions and spontaneous behaviour change (see Supplementary Fig. 17 for contact matrices differences between the two waves when accounting for in-person attendance).

Similar to a previous study run in late 2022 in the UK, Belgium, and the Netherlands, we found that the mean number of contacts in Italy in 2022/2023 has increased compared to those recorded in 2021[35,39,40] (Supplementary Tables 4 and 5). In line with other recent contact studies, we identified a positive association between the number of reported contacts and higher education levels, higher income, larger household size, lower age, and COVID-19 vaccination[41–43]. We also note that, compared to the pre-pandemic POLYMOD collection (run in April 2006)[13], respondents reported fewer social contacts. However, it is not trivial to understand whether this difference reveals a change in social behaviour (number of interactions, contact characteristics such as the amount of face-to-face communication), or methodology-induced differences (e.g., online vs paper data collections[41]; see also Supplementary Table 3 for a detailed methodological comparison between surveys).

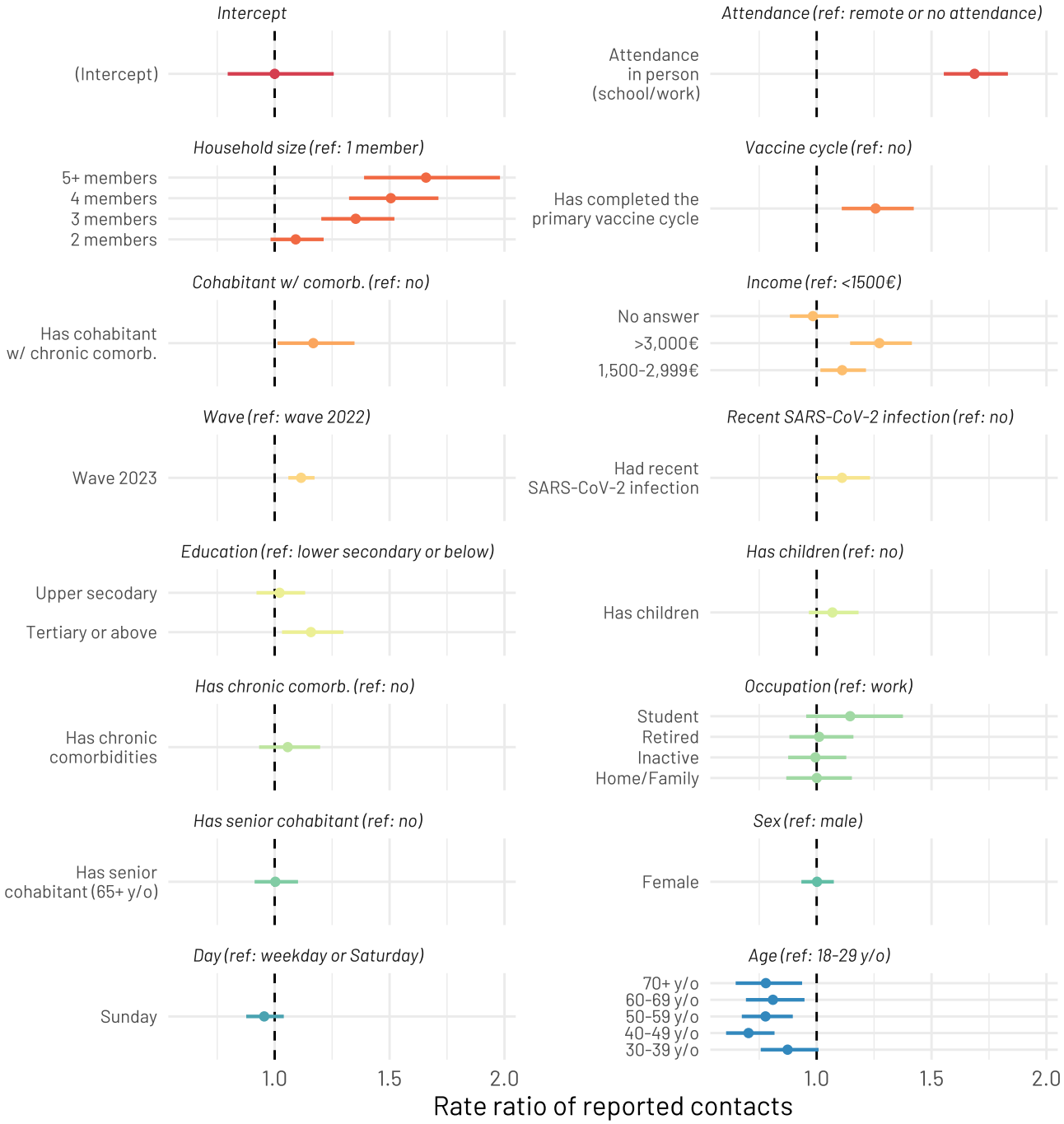


Fig. 3 | Rate ratios for the number of contacts in the adult population associated with respondent's characteristics. Rate ratios higher (lower) than one indicate a higher (lower) average number of contacts for the given covariate relative to the reference. Points: mean rate ratio; lines: 95%CI. Results are drawn from $n = 4492$ adults' survey responses.

Importantly, we found that the strongest determinant of the total number of contacts was in-person attendance at work or school. Other contact studies have found a similar relationship between workers and non-workers, but our focus on work-from-home and distance learning on the number of contacts allowed us to provide quantitative insights on potential governmental interventions acting on work/school in-person attendance. We quantified the reduction in transmissibility of a respiratory virus transmitted through direct contact or shared closed spaces that could be allowed by combinations of school closures and working-from-home mandates (or the suspension of non-essential economic activities altogether). In agreement with previous findings, we found that suspending in-person education has a generally stronger impact on transmissibility (up to 20% reduction when applied to all education levels in the absence of measures on work attendance)[44,45] than reducing the in-person workforce (up to 5.5% when all non-essential productive sectors are suspended). A combination of both interventions at the maximum level (similar to what was implemented during the Italian lockdown in March–April 2020) is expected to contribute to a reduction of the transmissibility of up to about 30% in the absence of other preventive measures such as mask use, isolation of diagnosed individuals, tracing and quarantining of contacts, ventilation of closed spaces, restrictions on other social contacts, and spontaneous protective behaviour. The suspension of non-essential economic activities always had a limited (< 5%) additional effect on further reducing transmissibility when compared to sustainable work-from-home mandates.

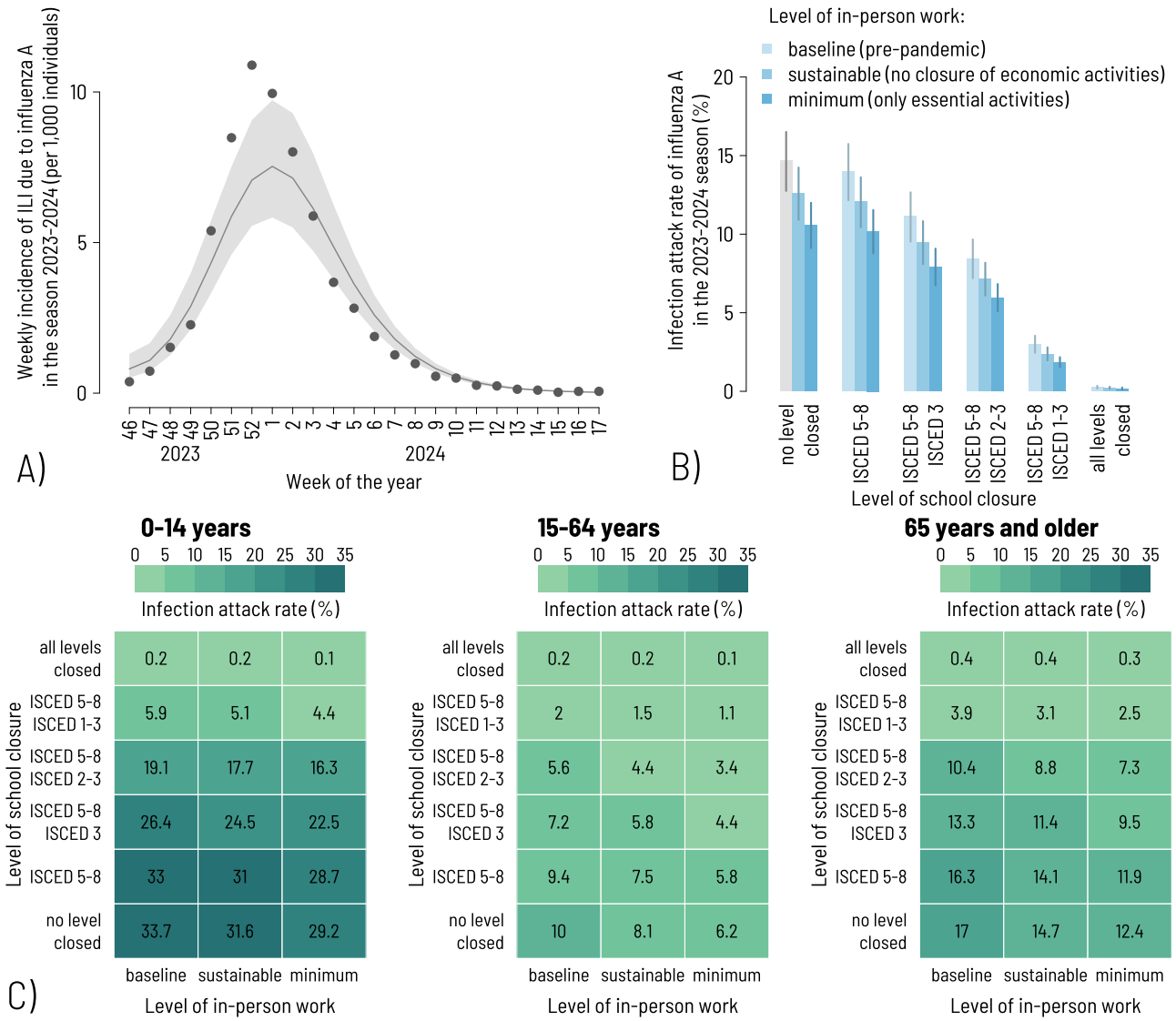


Fig. 4 | Impact of school and workplace attendance scenarios on influenza A transmission in Italy, 2023–2024. A Weekly incidence of influenza-like illness (ILI) attributable to influenza A during the 2023–2024 season (per 1,000 individuals), as reported by the InfluCast web platform[34] (dark grey points), and mean weekly incidence estimated by the model (solid line). Shaded areas represent 95% Prediction Intervals (PI) of model estimates. **B** Overall infection attack rate (%) of influenza A in the 2023–2024 season under alternative intervention scenarios combining different levels of school closures (including distance-learning mandates) and in-person work. The grey bar corresponds to the baseline full in-person attendance scenario (used for model calibration), in which the proportion of in-person workers is set to pre-pandemic levels and students at all education levels attend in person. Bars represent mean model estimates; vertical segments represent 95% PI of model estimates. **C** Mean age-specific infection attack rates under intervention scenarios combining different levels of school closures and in-person work. Age groups are defined as 0–14 years, 15–64 years, and ≥ 65 years. Mean model estimates and 95% PI are computed from $n = 80{,}000$ posterior parameter samples obtained from the MCMC calibration.

Distance learning is a highly debated measure due to its implications on the quality of education and psychological well-being of children and young adults, and on the increased burden on parents who need to rebalance childcare with their work responsibilities. In particular, closing lower educational levels poses stronger challenges to families, since young children engage less effectively in distance learning[46] and require a higher intensity of care. In this context, a relevant finding of this study is that maintaining in-person attendance for early childhood education (children aged 0–5 years) minimally affects the effectiveness of the intervention. We acknowledge, however, that since questionnaires for young children were compiled by their legal guardians, they may be more prone to biases due to second-hand reporting of the number of contacts; therefore, we advise caution in the interpretation of this result.

In the context of social contact studies for epidemiological modelling, special attention needs to be placed on the definition of contacts. Traditional definitions, such as those proposed by Mossong et al.[13] or Coletti et al.[19], emphasise the importance of physical and conversational interactions. However, COVID-19 highlighted the importance of airborne transmission in shared indoor spaces[47–49]. To account for this, we included indirect contacts due to co-location in closed spaces within the definition of contact in the main analysis. One limitation of this choice is that details on the contact (e.g., their age) would be difficult to recall for all co-located contacts (for example, customers attending the same restaurant or bar), given the lack of personal interaction and their potentially large number. Therefore, we chose not to collect detailed information on indirect contacts to avoid long survey completion times resulting in high dropout rates or low-quality responses. Information on the age of indirect contacts was inferred based on the details provided for direct contacts. Nonetheless, a sensitivity analysis where we considered only direct contacts provided consistent results with those of the main analysis (reported in the Supplementary Information).

Our findings suggest that the impact of work-from-home and distance learning measures on the reproduction number may depend on the epidemiological characteristics of the pathogen considered, such as the age-specific susceptibility to infection. In particular, interventions targeting schools tend to be more effective for pathogens with higher susceptibility among younger age groups, while measures acting on in-person work attendance have a more limited effect.

As such, results may need to be recalibrated to the features of the actual pathogen for which such measures are taken into consideration. However, data collected and made available through this study make such a reassessment relatively straightforward once the characteristics of the pathogen are known. For a more comprehensive assessment of age-specific reductions in transmissibility, it would have been valuable to explicitly disaggregate the 80+ age group, as this population is often the most vulnerable to severe disease outcomes. In our dataset, however, the number of respondents for this population stratum was insufficient (fewer than 50 survey responses) for robust separate estimates.

Although we believe that qualitative results from this study may hold for countries with similar socio-demographic and economic structures, we caution against their direct extrapolation to other geographical settings, given heterogeneities in educational systems, workplace structures, and social interactions at work, household composition, age-specific population size, and contact patterns. Moreover, the scenario analysis considered in this study simplifies the complex interdependencies between social settings. In particular, the assumption that schools and workplace in-person attendance can vary independently represents a limitation. In reality, closures of early education levels (e.g., kindergartens or primary schools) would likely entail a concurrent reduction in workplace attendance, as parents or other caregivers need to provide childcare. As a consequence, the reduction in transmissibility estimated under scenarios assuming the closure of all school levels likely represents a lower bound of the effect achievable in real-world conditions.

This research provides data across multiple sociodemographic strata on social contact patterns in Italy after the COVID-19 emergency, and analytics identifying the effect of socio-economic and demographic determinants on the number of experienced social contacts. These results were combined with data on school enrolment and in-person work attendance to provide estimates of the potential impact of public health interventions involving the educational and productive sectors. Estimates of this kind can support considerations on the balance between the expected epidemiological benefits and their societal costs.

Data availability

Social contact data collected in this study have been prepared in a format suitable for public release and are available on the Social Contact Data website (https://www.socialcontactdata.org) and in a dedicated repository on Zenodo (https://zenodo.org/records/17579537). The dataset is deposited under the name "MixIT: Post-pandemic social contacts in Italy" with https://doi.org/10.5281/zenodo.17579536[50].

Code availability

The code used to perform the statistical and modelling analyses, as well as to generate all figures presented in the main text and Supplementary Information, is available in a public GitHub repository (https://github.com/LLucchini/MixIT-social-contact-data-Italy). The repository is deposited under the https://doi.org/10.5281/zenodo.18773366[51].

Received: 26 February 2025; Accepted: 11 March 2026;
Published online: 04 May 2026

References

1. Perra, N. Non-pharmaceutical interventions during the COVID-19 pandemic: A review. *Phys. Rep.* **913**, 1–52 (2021).
2. Mendez-Brito, A., El Bcheraoui, C. & Pozo-Martin, F. Systematic review of empirical studies comparing the effectiveness of non-pharmaceutical interventions against COVID-19. *J. Infect.* **83**, 281–293 (2021).
3. Parolin, Z. & Lee, E. K. Large socio-economic, geographic and demographic disparities exist in exposure to school closures. *Nat. Hum. Behav.* **5**, 522–528 (2021).
4. Fink, G., Tediosi, F. & Felder, S. Burden of Covid-19 restrictions: National, regional and global estimates. *eClinicalMedicine* **45**, 101305 (2022).
5. Lichand, G., Doria, C. A., Leal-Neto, O. & Fernandes, J. P. C. The impacts of remote learning in secondary education during the pandemic in Brazil. *Nat. Hum. Behav.* **6**, 1079–1086 (2022).
6. United Nations. COVID-19 to slash global economic output by $8.5 trillion over next two years. United Nations https://www.un.org/en/desa/covid-19-slash-global-economic-output-85-trillion-over-next-two-years.
7. Jarvis, C. I. et al. Quantifying the impact of physical distance measures on the transmission of COVID-19 in the UK. *BMC Med.* **18**, 124 (2020).
8. Trentini, F. et al. Investigating the relationship between interventions, contact patterns, and SARS-CoV-2 transmissibility. *Epidemics* **40**, 100601 (2022).
9. Guzzetta, G. et al. Impact of a Nationwide Lockdown on SARS-CoV-2 Transmissibility, Italy. *Emerg. Infect. Dis.* **27**, 267–270 (2021).
10. Manica, M. et al. Impact of tiered restrictions on human activities and the epidemiology of the second wave of COVID-19 in Italy. *Nat. Commun.* **12**, 4570 (2021).
11. Marziano, V. et al. Retrospective analysis of the Italian exit strategy from COVID-19 lockdown. *Proc. Natl. Acad. Sci.* **118**, e2019617118 (2021).
12. Mistry, D. et al. Inferring high-resolution human mixing patterns for disease modeling. *Nat. Commun.* **12**, 323 (2021).
13. Mossong, J. et al. Social Contacts and Mixing Patterns Relevant to the Spread of Infectious Diseases. *PLOS Med* **5**, e74 (2008).
14. Prem, K., Cook, A. R. & Jit, M. Projecting social contact matrices in 152 countries using contact surveys and demographic data. *PLOS Comput. Biol.* **13**, e1005697 (2017).
15. Melegaro, A. et al. Social Contact Structures and Time Use Patterns in the Manicaland Province of Zimbabwe. *PLOS ONE* **12**, e0170459 (2017).
16. Hale, T. et al. A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker). *Nat. Hum. Behav.* **5**, 529–538 (2021).
17. Lucchini, L. et al. Living in a pandemic: changes in mobility routines, social activity and adherence to COVID-19 protective measures. *Sci. Rep.* **11**, 24452 (2021).
18. Aguolu, O. G. et al. Comprehensive profiling of social mixing patterns in resource poor countries: A mixed methods research protocol. *PLOS ONE* **19**, e0301638 (2024).
19. Coletti, P. et al. CoMix: comparing mixing patterns in the Belgian population during and after lockdown. *Sci. Rep.* **10**, 21885 (2020).
20. Kiti, M. C. et al. Early Release–Social Contact Patterns in Rural and Urban Settings, Mozambique, 2021–2022. *Emerg. Infect. Dis. J.–CDC* **31**, 94 (2025).
21. Mathieu, E. et al. Coronavirus Pandemic (COVID-19). *Our World Data* https://ourworldindata.org/covid-stringency-index (2020).
22. Wang, M. et al. Social contacts patterns relevant to the transmission of infectious diseases in Suzhou, China following the COVID-19 epidemic. *J. Health Popul. Nutr.* **43**, 58 (2024).
23. Jarvis, C. I. et al. Social contact patterns following the COVID-19 pandemic: a snapshot of post-pandemic behaviour from the CoMix study. *Epidemics* **48**, 100778 (2024).
24. Jeong, H. et al. Chronological trend of social contact patterns in Japan after the emergence of COVID-19. *J. Infect. Public Health* **18**, 102629 (2025).

25. Liang, Y. et al. Social contact patterns and their impact on the transmission of respiratory pathogens in rural China. *Infect. Dis. Model.* **10**, 439–452 (2025).
26. Eurostat. Overview–NUTS–Nomenclature of territorial units for statistics–Eurostat. https://ec.europa.eu/eurostat/web/nuts/overview.
27. Jiang, J. & Nguyen, T. *Linear and Generalized Linear Mixed Models and Their Applications*. (Springer, New York, NY, https://doi.org/10.1007/978-1-0716-1282-8 2021).
28. Eurostat. Educational attainment level and transition from education to work (based on EU-LFS). https://ec.europa.eu/eurostat/cache/metadata/en/edat1_esms.htm.
29. Diekmann, O., Heesterbeek, J. A. P. & Metz, J. A. J. On the definition and the computation of the basic reproduction ratio R0 in models for infectious diseases in heterogeneous populations. *J. Math. Biol.* **28**, 365–382 (1990).
30. Diekmann, O., Heesterbeek, J. A. & Roberts, M. G. The construction of next-generation matrices for compartmental epidemic models. *J. R. Soc. Interface* **7**, 873–885 (2009).
31. Merler, S. et al. Pandemic Influenza A/H1N1pdm in Italy: Age, Risk and Population Susceptibility. *PLOS ONE* **8**, e74785 (2013).
32. Hu, S. et al. Infectivity, susceptibility, and risk factors associated with SARS-CoV-2 transmission under intensive contact tracing in Hunan, China. *Nat. Commun.* **12**, 1533 (2021).
33. Trentini, F. et al. Characterizing the transmission patterns of seasonal influenza in Italy: lessons from the last decade. *BMC Public Health* **22**, 19 (2022).
34. Influcast. *Influcast* https://influcast.org/.
35. Gimma, A., Wong, K. L., Coletti, P. & Jarvis, C. I. CoMix social contact data (Italy). Zenodo https://doi.org/10.5281/zenodo.6362888 (2021).
36. Stefanelli, P. et al. Tracking the progressive spread of the SARS-CoV-2 Omicron variant in Italy, December 2021 to January 2022. *Eurosurveillance* **27**, 2200125 (2022).
37. Marziano, V. et al. Estimating SARS-CoV-2 infections and associated changes in COVID-19 severity and fatality. *Influenza Other Respir. Viruses* **17**, e13181 (2023).
38. Civil Protection Department. Coronavirus: the state of emergency ends on March 31. https://www.protezionecivile.gov.it/en/notizia/coronavirus-state-emergency-ends-march-31/.
39. United Nations. WHO chief declares end to COVID-19 as a global health emergency | UN News. https://news.un.org/en/story/2023/05/1136367 (2023).
40. Verelst, F. et al. SOCRATES-CoMix: a platform for timely and open-source contact mixing data during and in between COVID-19 surges and interventions in over 20 European countries. *BMC Med.* **19**, 254 (2021).
41. Leung, K., Jit, M., Lau, E. H. Y. & Wu, J. T. Social contact patterns relevant to the spread of respiratory infectious diseases in Hong Kong. *Sci. Rep.* **7**, 7974 (2017).
42. Manna, A., Koltai, J. & Karsai, M. Importance of social inequalities to contact patterns, vaccine uptake, and epidemic dynamics. *Nat. Commun.* **15**, 4137 (2024).
43. Wambua, J. et al. The influence of COVID-19 risk perception and vaccination status on the number of social contacts across Europe: insights from the CoMix study. *BMC Public Health* **23**, 1350 (2023).
44. Molina Grané, C. et al. SARS-CoV-2 transmission patterns in educational settings during the Alpha wave in Reggio-Emilia, Italy. *Epidemics* **44**, 100712 (2023).
45. Manica, M. et al. Estimating SARS-CoV-2 transmission in educational settings: A retrospective cohort study. *Influenza Other Respir. Viruses* **17**, e13049 (2023).
46. Tomasik, M. J., Helbling, L. A. & Moser, U. Educational gains of in-person vs. distance learning in primary and secondary schools: A natural experiment during the COVID-19 pandemic school closures in Switzerland. *Int. J. Psychol.* **56**, 566–576 (2021).
47. Peng, Z. et al. Practical Indicators for Risk of Airborne Transmission in Shared Indoor Environments and Their Application to COVID-19 Outbreaks. *Environ. Sci. Technol.* **56**, 1125–1137 (2022).
48. Zhao, X., Liu, S., Yin, Y., Zhang, T. & Chen, Q. Airborne transmission of COVID-19 virus in enclosed spaces: An overview of research methods. *Indoor Air* **32**, e13056 (2022).
49. Bazant, M. Z. & Bush, J. W. M. A guideline to limit indoor airborne transmission of COVID-19. *Proc. Natl. Acad. Sci.* **118**, e2018995118 (2021).
50. Lucchini, L. & Marziano, V. MixIT: Post-pandemic social contacts in Italy. Zenodo https://doi.org/10.5281/zenodo.17579537 (2025).
51. Lucchini, L. LLucchini/MixIT-social-contact-data-Italy: MixIT: post-pandemic social contact data for Italy. Zenodo https://doi.org/10.5281/zenodo.18773367 (2026).
52. Iozzi, F. et al. Little Italy: An Agent-Based Approach to the Estimation of Contact Patterns- Fitting Predicted Matrices to Serological Data. *PLOS Comput. Biol.* **6**, e1001021 (2010).

Acknowledgements

L.L., C.C., F.T., V.O., E.D.A., D.B. acknowledge funding from the ERC Consolidator Grant IMMUNE (no. 101003183). Researchers from the Bocconi Covid Crisis Lab acknowledge funding from the Romeo and Enrica Invernizzi Foundation. This research was supported by funding from the Fondazione Valorizzazione Ricerca Trentina (VRT), project COVIDVAX (V.M. and G.G.), by EU funding under NextGenerationEU-MUR PNRR Extended Partnership Initiative on Emerging Infectious Diseases, project number PE00000007 INF-ACT (CUP H93C22000640007, M.M. and S.M.; "Behave-Mod" CUP I83C22001810007, A.M.) and by funding from EU grant 101045989 VERDI (P.P.).

Author contributions

Conceptualization: L.L., V.M., S.M., A.M., Questionnaire design: L.L., V.M., F.T., C.C., V.O., M.M., P.P., D.B., G.G.; Data collection and quality control: L.L., V.M., and V.O.; Data cleaning and statistical analysis: L.L., F.T., E.D.A., C.C.; Implementation of experiments: L.L. and V.M.; Critical review of experiments results: G.G., M.M., P.P., M.A., S.M., A.M.; Writing original draft: L.L., V.M., and G.G.; Writing review and editing, L.L., V.M., F.T., C.C., E.D.A., V.O., M.M., P.P., D.B., G.G., M.A., A.M., S.M.

Competing interests

The authors declare no competing interests.

Additional information

Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s43856-026-01543-4.

Correspondence and requests for materials should be addressed to Alessia Melegaro.

Peer review information *Communications Medicine* thanks the anonymous reviewers for their contribution to the peer review of this work. Peer review reports are available.

Reprints and permissions information is available at http://www.nature.com/reprints

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Open Access This article is licensed under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License, which permits any non-commercial use, sharing, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if you modified the licensed material. You do not have permission under this licence to share adapted material derived from this article or parts of it. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit http://creativecommons.org/licenses/by-nc-nd/4.0/.

© The Author(s) 2026