Proceedings of the 2022 Winter Simulation Conference
B. Feng, G. Pedrielli, Y. Peng, S. Shashaani, E. Song, C.G. Corlu, L.H. Lee, E.P. Chew, T. Roeder, and P. Lendermann, eds.

ASSESSING TRANSMISSION RISKS OF SARS-COV-2 OMICRON VARIANT IN U.S. SCHOOL FACILITIES AND MITIGATION MEASURES

Yifang Xu
Shuai Li
Qiang He

Department of Civil and Environmental Engineering
University of Tennessee, Knoxville
851 Neyland Drive
Knoxville, TN 37996, USA

Siyao Zhu

Department of Civil and Systems Engineering
Johns Hopkins University
3400 N. Charles St
Baltimore, MD 21218, USA

Jiannan Cai

School of Civil & Environmental Engineering, and Construction Management
The University of Texas at San Antonio
501 W César E Chávez Blvd
San Antonio, TX 78207, USA

ABSTRACT

The emergence of the SARS-CoV-2 Omicron variant raises concerns for school operations worldwide. The Omicron variant spread faster than other variants that cause COVID-19, and breakthrough infections are reported in vaccinated people. Schools are hotbeds for the transmission of the highly contagious virus. Therefore it is crucial to understand the risks of Omicron transmission and the effectiveness of different measures to prevent the surge of infection cases. This study estimates the risks of airborne transmission and fomite transmission of Omicron variants using simulations and the data of 11,485 public and private schools in the U.S. It also analyzes the impact of different mitigation measures on limiting airborne transmission and fomite transmission risks in schools. It was found that the Omicron variant caused relatively high infection risks in schools. The risk of airborne transmission is nine times higher than fomite transmission. The effective mitigation measures can significantly decrease the transmission risk.

1 INTRODUCTION

The original severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) strain was first identified as the virus that causes the outbreak of the coronavirus disease 2019 (COVID-19). The outbreak of COVID-19 spread rapidly around the world, and the coronavirus is continuously evolving during the pandemic. The Omicron variant is an emerging variant of SARS-CoV-2 and has become the dominant variant that accounts for the spread of COVID-19 against all other variants. The variant was first detected in South Africa in 2021(WHO 2021), and resulted in an unprecedented outbreak in SARS-CoV-2 cases around the world. Compared with the Delta variant, the other rapidly spread coronavirus variant, Omicron multiplied around 70 times faster in the bronchi (Hui et al. 2022), and is found to be 2 to 3 times more contagious (Klompas and Karan 2022). Although generally, Omicron infection causes less severe cases than other variants, the hyper-transmissibility in the crowd could overwhelm the healthcare system since some of the cases may develop severe symptoms and need hospitalization. Particularly, schools are identified at high risk of Omicron transmission due to the crowded and poorly-ventilated environment, and the inevitable contact and communication activities among students and teachers. The potential outbreak of COVID-19 during the Omicron surge triggers concerns about student health and school environment, and proper actions are needed to control the Omicron transmission in schools. It is reported that the current vaccines are effective at preventing severe symptoms such as hospitalizations and deaths due to infection with the Omicron variant, CDC indicates that breakthrough infections can occur and develop symptoms even for fully vaccinated people (CDC 2022a). Besides, the immunity through vaccination remains unclear since some variants reduce the efficacy of vaccines and lead to reinfection (Jimenez et al. 2022). Thus, despite getting vaccinated, other mitigation measures are required to curb the transmission of SARS-CoV-2 variants in K-12 schools.

Several studies have demonstrated that the Omicron variant, like other SARS-CoV-2 variants, can be transmitted via air (Cheng et al. 2022) and fomite touching (Pitol and Julian 2021; Sobolik et al. 2022). For airborne transmission, the infectious aerosols travel over long distances through the air, and susceptible hosts may get infected by inhaling the infectious aerosols (WHO 2020). The mitigation measures to reduce airborne transmission include increasing air ventilation to dilute the aerosols, implementing filters in HVAC systems, and adopting social distance measures such as partial online learning. For the fomite-mediated transmission, an infected person’s shedding or touching contaminated a surface. Susceptible hosts may get infected by touching the contaminated surface and pass the pathogens to the susceptible sites such as mucous membranes. The mitigation measures to curb fomite-based transmission include surface cleaning, hand cleaning, and dedensification measures to reduce the number of index cases, such as partial online learning. However, as an emerging variant, there are lack of data and relevant studies regarding Omicron transmission in nationwide schools.

To close the gap, this study estimated the airborne infection and fomite-based transmission risk of Omicron variant for 111,485 public and private U.S. schools, and evaluated the impact of different mitigation measures to control the transmission of Omicron variant. Simulation methods were used to model the two pathways, including airborne transmission route and fomite transmission route to comprehensively demonstrate the transmission of the new variant in school environment. For each transmission route, several commonly-used mitigation measures are selected to illustrate the effectiveness of different school operation strategies. The results of this study provide insights for school and government policymakers regarding the effective mitigation measures based on current local epidemic situation and school characteristics, and provide recommendations to control the airborne and fomite transmission of the SARS-CoV-2 Omicron variant in school environment.

2 METHODOLOGY

2.1 Data Retrieval

More than 110,000 K-12 schools across the U.S. were analyzed in this study. The characteristics of each school was retrieved from the statistical data acquired from National Center for Education Statistics (NCES 2021). Public schools were categorized into five school levels and private schools were categorized into three school levels. The school buildings’ occupant density was manually collected and estimated from typical schools, and the detailed process was introduced in our previous paper (Xu et al. 2021). The current pandemic situation was identified by the latest data of COVID-19 cases reported by the CDC (2022b). CDC indicated that Omicron is the current dominant variant among all SARS-CoV-2 variants and accounts for almost all the COVID-19 cases (CDC 2022c).

2.2 Airborne Transmission Modeling

2.2.1 Airborne Infection Risks Assessment

The infection risk of airborne transmission was defined as the probability of a susceptible student being infected by inhaling infectious aerosols in the air after one school day. The airborne infection risk was modeled using Gammaitoni–Nucci (G-N) equation (Gammaitoni and Nucci 1997). The G-N equation computes the airborne infection risk (P_A) using equation (1), where I is the number of index cases, V is the school volume (m^3), N is the virus removal rate (hr^{-1}), t is the school operation hour (hr), p is the student breathing rate (m^3/hr), and φ is the quanta generation rate ($quanta/hr$).

$$P_A = 1 - e^{-\frac{pI\varphi}{V}\left(\frac{Nt+e^{-Nt}-1}{N^2}\right)} \tag{1}$$

In this study, I was estimated based on current COVID-19 cases, and was computed as the product of school population and the current county infection rate. V was retrieved from school data. t was the school operation hour retrieved from the state data (NCES 2008). N is the virus removal rate, including the virus removal due to air ventilation ($\lambda_{ventilation}$) and air filtration ($k_{filtration}$) if filters are implemented in the HVAC system. The baseline $\lambda_{ventilation}$ was set as 2 hr^{-1} (Batterman et al. 2017). p was estimated based on the age group in a school. φ was computed using equation (2) (Buonanno et al. 2020), where α is the conversion factor of the transmissibility between new variants and the original SARS-CoV-2 strain. c_v is the viral load in sputum, c_i is a unit conversion factor, indicating the ratio between the quantum and dose, $V_{d,i}$ is the volume of a droplet calculated based on droplet diameter distribution, and $N_{d,i,j}$ is the concentration of the droplet size i regarding the expiratory activity j.

$$\varphi = \beta c_v c_i p\left(\sum_{i=1}^{4} V_{d,i} N_{d,i,j}\right) \tag{2}$$

To describe the hyper-transmissibility of the Omicron variant, a new parameter β was introduced in the model. β was set to be 3.3 to reflect the increased transmissibility of the Omicron variant compared with the original SARS-CoV-2 strain (Lyngse et al. 2022); c_v was set as 10^9 RNA virus copies mL^{-1}, and c_i was set as 0.02 (Buonanno et al. 2020); p is the student breathing rate estimated based on school level (m^3/h). Generally, p increases as the student age increases; $N_{d,i,j}$ was estimated as the droplet viral concentration of for speaking activity. The speaking activity was considered as the activity between voiced counting and unmodulated vocalization.

2.2.2 Airborne Transmission Control Measures

The impact of three mitigation measures and the impact of the combination of the mitigation measures was evaluated in this study. The mitigation measures including: 1. Implementing MERV 13 filters to HVAC systems (AM1); 2. Increasing air ventilation rate ($\lambda_{ventilation}$) by 100% (AM2); 3. Adopting hybrid learning and ask 50% of the students learning online (AM3); 4. Combination of mitigation measures, including AM1 + AM2, AM1 + AM3, AM2 + AM3, and AM1 + AM2 + AM3.

The impact of AM1 was modeled by modifying the particle filtering rate caused by filtration ($k_{filtration}$) in equation (1). $k_{filtration}$ can be computed using equation (3) (Buonanno et al. 2020), where $\lambda_{recirculated}$ indicates the flow rate of the air recirculated through HVAC filters , set as 6.4 hr^{-1} (Azimi and Stephens 2013), and η_{filter} is the filtration efficiency of the filters. η_{filter} can be estimated according to the minimum efficiency reporting value (MERV) of the filter and the particle size based on ASHRAE standard (Standard 52.2-2017).

$$k_{filtration} = \lambda_{recirculated}\, \eta_{filter} \tag{3}$$

The MERV 13 filter's filtration efficiency was set to be 67.5%, assuming that half the particle distribution is 50% from 0.3 to 1 μm in size and 50% are 1 to 3 μm. The assumption is based on an experimental result that more than 50% of the aerosols of SARS-CoV-2 are smaller than 2.5 μm (Morawska and Cao 2020). The impact of M3 was modeled by reducing half of the number of infectors while increasing occupancy density by 100%.

2.3 Fomite-Mediated Transmission Modeling

2.3.1 Fomite-Mediated Transmission Risk Assessment

The risk of fomite-based transmission in this study indicated the probability of susceptible students getting infected by fomite-mediated pathways. For the fomite-mediated transmission, a surface is contaminated when infected people shed or touch on the surface of objects in the school, such as desks and doorknobs. Susceptible hosts may get infected by touching the contaminated surface and inoculate the pathogens through mucous membranes via actions such as mouth touching. Susceptible hosts with contaminated hands can also spread the pathogens via hand-surface contacts. In this study, an Environmental Infection Transmission System (EITS) modeling framework (Kraay et al. 2018) was employed to analyze the spread of Omicron via fomite transmission. The EITS model divided individuals to be susceptible (S), infectious (I), and removed (R) hosts. The pathogens surviving in the environment are either contaminate a fomite (F) or hands (H). Pathogen exchange occurs through hand touching behavior. Pathogens are shed to Hands of I (H_I) via excretion (e.g., cough, sneeze). The pathogens excreted on H_I can be further transferred to object surfaces by fomite touching behavior. The hands of S and R (H_S, H_R) become contaminated by touching the contaminated surface. Pathogens are transmitted dynamically between F and H. S may get infected by self-inoculation via contaminated H_S. The epidemic dynamics can be modeled by ordinary differential equations, and the risk of fomite-mediated transmission in a typical school day (P_F) can be expressed using equation (4) (modified based on Kraay et al. 2018).

$$\begin{cases} P_F = \frac{K_F + K_H}{N - I} \\ K_F = tIa_F P_{inoculation} P_{pickup} P'(0) \\ K_H = tIa_H P_{inoculation} P_{pickup} P_{deposit} P'(0) \\ P_{inoculation} = \frac{\rho\chi}{\mu_H + \rho_{HF} + \rho\chi + \theta_H} \\ P_{pickup} = \frac{\frac{N\rho_{FH}}{N\rho_{FH} + \mu_F + \theta_F}}{1 - \frac{N\rho_{FH}}{(N\rho_{FH} + \mu_F + \theta_F)} \frac{\rho_{HF}}{(\mu_H + \rho_{HF} + \rho\chi + \theta_H)}} \\ P_{deposit} = \frac{\rho_{HF}}{\mu_H + \rho_{HF} + \rho\chi + \theta_H} \end{cases} \tag{4}$$

In this model, S may get infected via two fomite transmission routes, the direct fomite contamination route (CR_F) and the hand-fomite contamination route (CR_H). K_F indicates the number of S getting infected via CR_F, K_H is the number of S getting infected via CR_H. P_F is defined as the proportion of S being infected via fomite-mediated transmission (CR_F and CR_H) after t hours of exposure. $P_{inoculation}$ is the proportion of chance that the susceptible people get self-inoculation; P_{pickup} is the pathogens picked up by hands from the contaminate surface in percentage; $P_{deposit}$ is the proportion of pathogens excreted to hands that are transmitted to the fomites via touching behavior. $P'(0)$ indicates the infectivity of the pathogens.

To simulate the fomite transmission of the Omicron variant, the parameters of SARS-CoV-2 original strain were used for most of the pathogen-specific parameters, while the increased transmissibility of the Omicron variant was considered as 10-fold viral shedding concentrations (Sobolik et al. 2022). The increased shedding concentrations are employed to estimate the viral shedding rate of the Omicron variant. In this study, the main way of virus shedding was coughing. The number of viruses shed via coughing from the respiratory tract per hour per infectious individual is defined as the shedding rate. Equation (5) (Li et al. 2021) shows how the shedding rate was calculated, where $V_{droplet}$ is the volume of an infectious droplet, F_{cough} is the frequency of coughing, $N_{droplet}$ is the amount of shed drops per cough, and L is the viral load in saliva.

$$\alpha = V_{droplet} \times F_{cough} \times N_{droplet} \times L \tag{5}$$

The viral load of SARS-CoV-2 Omicron variant is set to be 7.8 $log10\ RNA\ copies/mL$ (Sobolik et al. 2022), and the diameter of the infectious droplet was assumed to be 100 μm, 12 times per hour was set for F_{cough}, and $N_{droplet}$ was set to be 2000 per cough. The viral shedding rate of Omicron was computed as 7.93E5. The information on other pathogen-specific parameters could be found in Table 1.

Table 1: Input parameters to the airborne transmission model.

Parameter	Units	Description	Values	References
t	hr	Exposure time	School day	(NCES 2008)
α	Pathogens/ (hr × people)	Infectious individuals excrete pathogens at rate α	7.93E05	Calculation
ρ	/min	Inoculation	0.8	(Sobolik et al. 2022)
μ_F	/day	Viral decay rate on F	0.18 (0.14, 0.22)	(Kwon et al. 2021)
μ_H	/min	Viral decay rate on H	1.195 (0.92, 1.47)	(Nicas and Best 2008)
τ_{FH}	proportion	Viral transfer fraction from F to H	0.217 (0.067,0.367)	(Lopez et al. 2013)
τ_{HF}	proportion	Viral transfer fraction from H to F	0.025	(Nicas and Jones 2009)
φ_H	proportion	Pathogen excreted to H	0.15	(Kraay et al. 2018)
φ_F	proportion	Pathogen excreted to F	$1 - \varphi_H$	
π	unitless	Dose-response parameter	6.58E-06	
θ_F	/hr	Frequency of fomite cleaning	0 (0, 1)	Estimation
θ_H	/hr	Frequency of hand cleaning	0 (0, 1)	Estimation
S_{Finger}	m2	Surface area of three finger tips touching a surface	0.00042	(Bouwknegt et al. 2015)
aH	Pathogens/ (hr × people)	rate pathogens added to H	$\alpha\varphi_H$	(Kraay et al. 2018)
aF	Pathogens/ (hr × people)	rate pathogens added to F	$\alpha\varphi_F$	(Kraay et al. 2018)
λ	proportion	accessible surface	0.3	
ρ_T	/day	rate of fomite touching	60	(Kraay et al. 2018)

2.3.2 Fomite-Mediated Transmission Control Measures

The impact of three mitigation measures and the impact of the combination of the mitigation measures on fomite transmission control was evaluated in this study. The mitigation measures including: 1. Building hygiene once per day (FM1); 2. Hand washing once per hour (FM2); 3. 50% of students learning online; 4. Combination of mitigation measures, including FM1 + FM2, FM1 + FM3, FM2 + FM3, and FM1 + FM2 + FM3.

3 RESULTS

3.1 Assessment of School Airborne Infection Risk

Figure 2 presents the Omicron airborne infection risk of each state under different control measures. The average airborne infection risks of counties within a state were used to calculate the mean airborne infection risk of the state. The range of the state airborne infection risk represents the difference between the maximum and minimum airborne infection risks of that state. Outliers exceeding four times the standard deviation of the counties in a state were removed before generating the range. The county level airborne infection risk was computed based on the current Omicron epidemic situation and the school characteristics. For all states, schools using baseline ventilation rate have higher average airborne infection risk, and the overall average airborne infection risk under this scenario was 4.51%. A wider range of airborne infection risks was revealed in the baseline situation as well. More than 90% of the states had a greater than 2% of average airborne infection risk, which is higher than the infection risks in previous epidemic situations (e.g., the prevalence for original SARS-CoV-2 strain). This result indicates the necessity of implementing interventions to reduce the airborne infection risk of Omicron.

Kruskal–Wallis one-way analysis of variance (ANOVA) test was conducted to figure out if the impact of modeled mitigation measures was statistically significant (Kruskal and Wallis 1952). The One-way Kruskal–Wallis test is a nonparametric method for analyzing if there is a difference of the population medians among all the groups under one categorical variable. In this study, the groups were identified as different mitigation measures, and the categorical variable was the airborne infection risks. A Kruskal–Wallis test was conducted to demonstrate the significance of different mitigation strategies. The p-value of the test was nearly 0, indicating that the null-hypothesis of same median among all groups can be rejected. The result demonstrated that there were significant differences among the mitigation strategies within 99% confidence interval (CI). A Conover squared ranks test was conducted as the post-hoc comparison to identify significant differences between pairs of groups (Conover and Iman 1981). The result indicated that among all the pairs of strategies, the difference between two combined control measures were insignificant with a p-value of 0.2809. The two combined measures are: implementing MERV 13 filtration and half of students studying remotely (AM1+AM3), and doubling the ventilation rate and half of students study remotely (AM2+AM3). All other pairs of strategies were found to be significantly different within 99% CI.

The impact of implementing MERV 13 filtration (AM1) indicated a significant improvement in reducing the airborne infection risk. The overall average airborne infection risk was reduced to 1.55% and the variation range of all states was reduced, which was illustrated by the smaller ranges. Airborne infection risk in more than 90% of states decreased to less than 2% under this control intervention. This control measure outperformed all three interventions as well. Double the ventilation rate (AM2) displayed a similar result as half of students study remotely (AM3). The overall average airborne infection risks under these two control measures were 2.40% and 2.30%, respectively. About 70% of states had the airborne infection risk lessen to 2%. The variation in airborne infection risk was reduced for all states as well.

Several states exhibited high average airborne infection risk. The result was mainly caused by the high county prevalence of the counties in the states. Specifically, states such as Alaska, Idaho, Kentucky, Maine, Rhode Island, and Vermont had more than twice the overall average airborne infection. Vermont exposed the highest average airborne infection risk among all states, which was 17.19% under baseline ventilation situations. The control measures reduced the airborne infection risk for all states, but the states with higher airborne infection risk still exceed the others under all three interventions.

School characteristics are another important aspect of influencing the county's airborne infection risk of Omicron, especially for the school levels. For instance, the infection risks vary among different school levels due to the difference of student beathing rate and school occupant density. Figure 1 shows the airborne infection risks of different school levels under various airborne transmission control measures. The risk was computed based on the nationwide school data and the range indicates the maximum and minimum risk for each school level. Data of more than two times the standard deviation from the mean were treated as outliers and removed before generating the result. The figure indicates that high school had the highest median airborne infection risk of 4.29% and the highest interquartile range (IQR) among all six levels of schools that were considered in this study. Elementary school showed the lowest median airborne infection risk and the lowest IQR among all school levels. Distinct control measures indicated a diverse impact on airborne infection risk. For individual controls, similar results are shown in Figure 2. MERV 13 (AM1) had the best solo control performance among all school levels. The median risk was reduced to 1.46% using AM1 in high school. The combination of AM1, AM2, and AM3 revealed the best performance among all control measures at all school levels. The median airborne infection risk in high school decreased to 0.56% under this combined control measure.

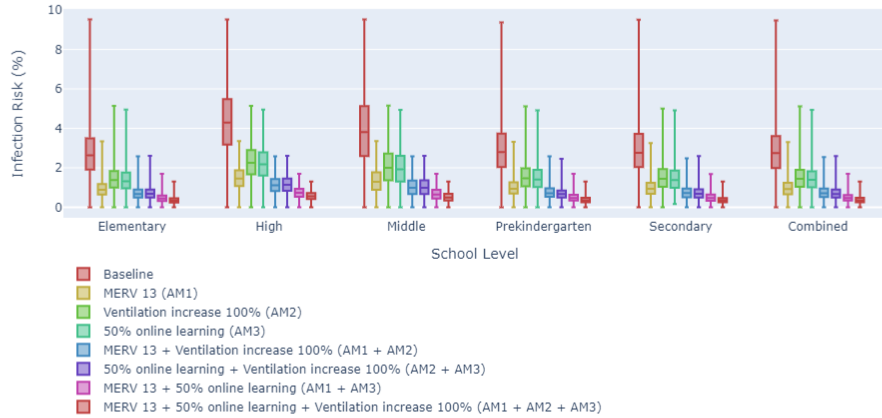

Figure 1: Airborne infection risks of different school levels under various airborne transmission control measures.

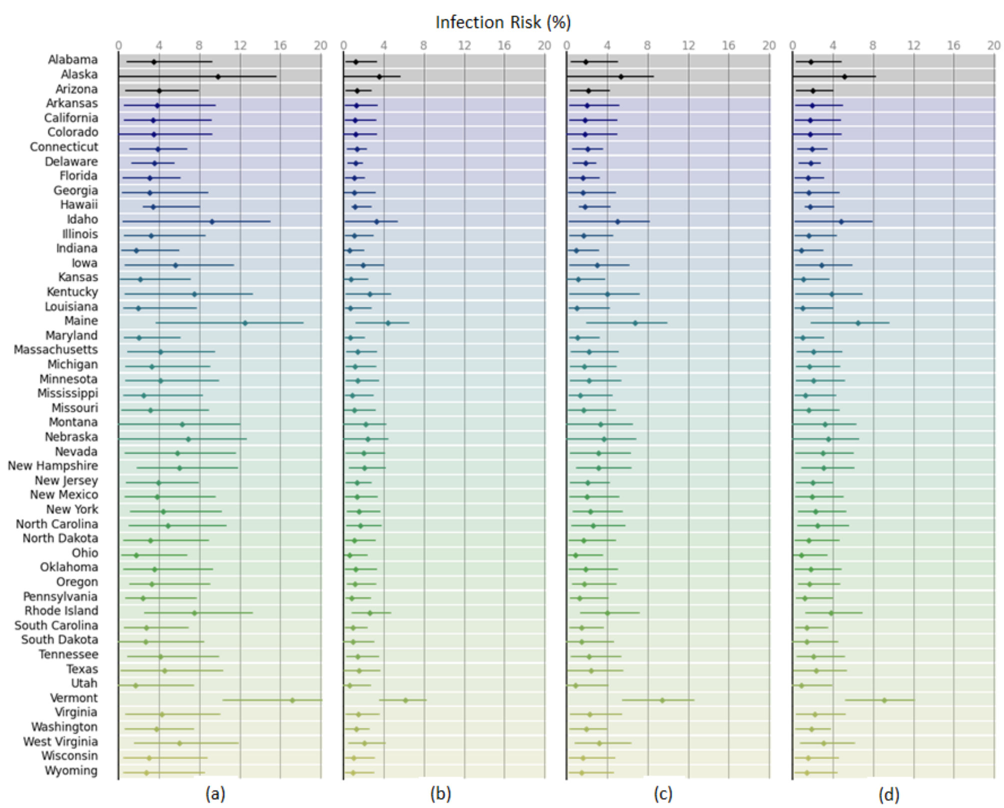

Figure 2: State airborne infection risk with distinct control measures: (a) the baseline situation; (b) applying MERV 13 filtration; (c) increasing the baseline air ventilation rate by 100%; (d) half students learning remotely.

3.2 Assessment of School Fomite Infection Risk

A similar analysis was performed on the fomite transmission data of Omicron. Figure 4 demonstrates the average fomite infection risk of all states in the U.S. Compared with the results in Figure 2, the overall average risk was less than the average airborne infection risk in all states. Under the baseline scenario of no surface cleaning and hand cleaning, more than 90% of states have less than 1% of average fomite infection risk. About 60% of the states had less than 0.5% of average fomite infection risk. The average fomite infection risk of all counties under the baseline scenario was 0.48%. This result indicates that for Omicron, people are more likely to get infected via airborne transmission than via fomite transmission. Similar with the statistical analysis for the airborne transmission control strategies, a one-way Kruskal–Wallis test and a post-hoc comparison were conducted. The p-value of the test was nearly 0, indicating that the mitigation strategies for the control of fomite transmission were statistically significant within 99% CI. The result of the pairwise comparison indicated that all the pairs of strategies were significantly different from others.

For different control measures, hand cleaning once per hour (FM2) and 50% of student learning online (FM3) showed similar results. The average fomite infection risks among all counties under FM2 and FM3 were 0.44% and 0.47%, respectively. There was no significant change in average fomite infection risk after applying FM2 and FM3. However, surface cleaning once per day (FM1) exhibited an evident impact on reducing the average fomite infection risk. The overall average fomite infection risk decreased to 0.22% when applying FM1. About 95% of states had less than 0.5% average infection risk and 100% of counties had less than 1% average fomite infection risk under this control measure. States with high average airborne infection risk also resulted in high average fomite infection risk. Vermont, Maine, Alaska, Idaho, Rhode Island, and Kentucky ranked top six on highest infection risk for both airborne and fomite transmission.

School characteristics were analyzed, and the result is illustrated in Figure 3. Unlike airborne transmission, there was no obvious difference displayed between school levels for fomite infection risk under the baseline scenario. The median fomite infection risks of all school levels were all-around 0.32%. The combined control measure of FM1 + FM2 + FM3 exhibited the best performance in reducing fomite infection risk for all school levels, which is similar to the airborne transmission result. A small distinction can be observed among different school levels after applying the combined intervention strategy. Prekindergarten reached the lowest median fomite infection risk of 0.039% and high school had the highest median fomite infection risk of 0.11%.

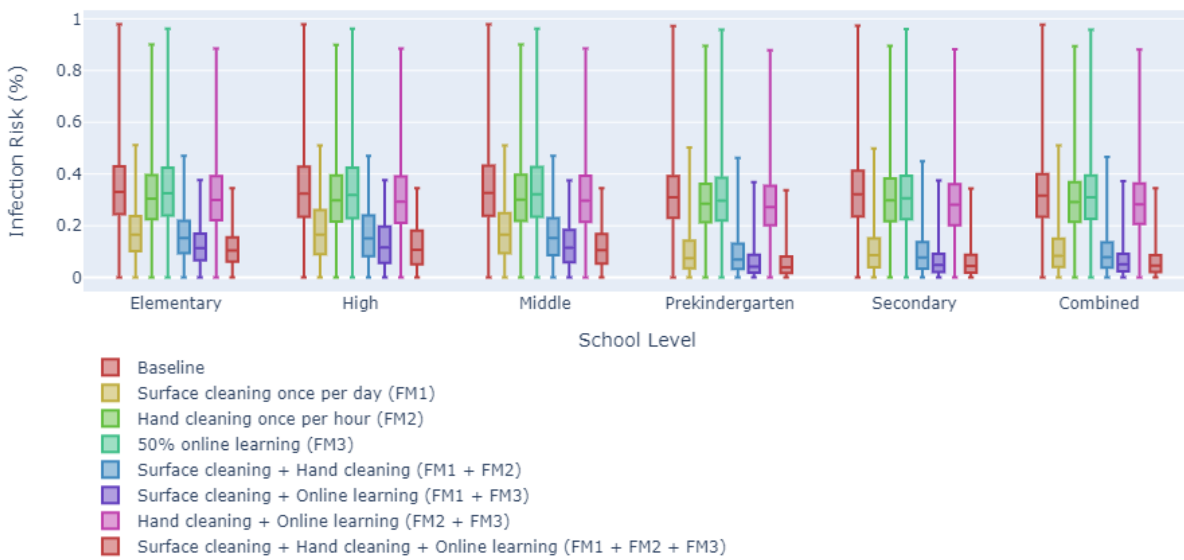

Figure 3: Fomite infection risks of different school levels under various fomite transmission control measures.

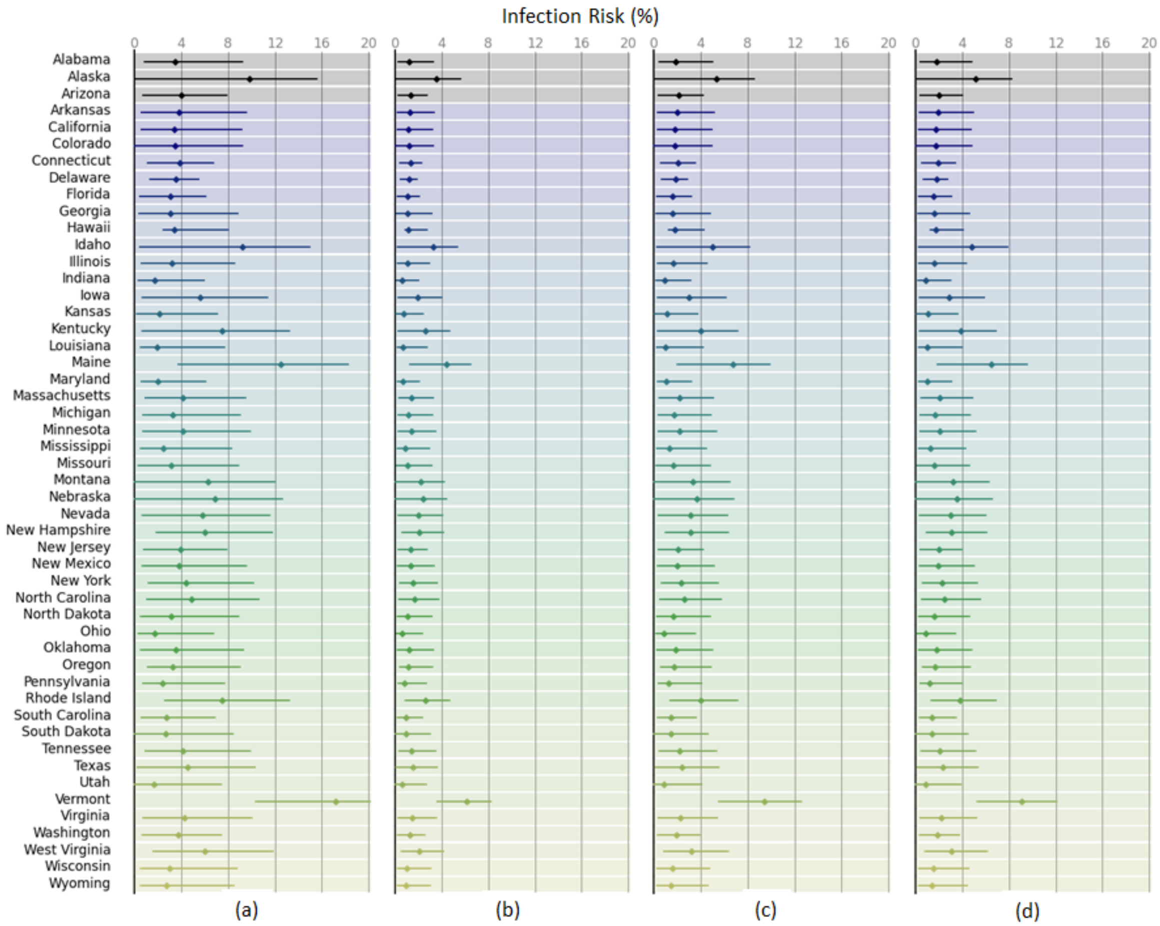

Figure 4: State fomite infection risk with distinct control measures: (a) the baseline situation; (b) surface cleaning once per day; (c) hand cleaning once per hour; and (d) half of students learning remotely.

4 DISCUSSION AND CONCLUSION

Two transmission pathways of the Omicron variant were simulated in this study due to the characteristics of schools and students. Schools are identified as crowded and poorly ventilated environments, which increase the risk of airborne transmission of various respiratory viruses, including SARS-CoV-2. Therefore, the airborne transmission route of Omicron was estimated, and the widely used operation strategies regarding the decrease of airborne infection risks during pandemics were included in the simulation and evaluated in the study. The operation strategies include ventilation increase, social distancing, filtration, and the combination of different strategies. Results indicate that county prevalence and school characteristics are the main features that affect the airborne infection risk. Under baseline ventilation, all states are exposed to high airborne infection risks, with an average infection risk of 4.51% of all states. Six states have way higher average airborne infection risk than other states. Meanwhile, school levels have an obvious impact on airborne infection risk. High schools showed the highest while elementary schools displayed the lowest median airborne infection risk among the six considered school levels. All the operation strategies resulted in significant improvement in decreasing airborne infection risk. Ventilation increase and social distancing demonstrated similar performance in reducing the infection risk, while filtration shows the best performance. This result is valid for all states and all school levels. All combined operation strategies showed better results than any individual operation strategy, while the combination of all three strategies exhibit the best performance and successfully reduced the median airborne infection risk to less than 0.5%.

Despite airborne transmission, since students at a young age are more liable to interact with their surrounding environment, viruses on the object surface are likely to transfer between hands and contaminated surfaces and occur self-inoculation. Thus, the fomite transmission route of Omicron was considered, and the effectiveness of mitigation measures such as surface cleaning, hand cleaning, and hybrid learning was assessed using a dynamic environmental infection transmission system. Results demonstrated that fomite transmission of Omicron has less impact on the infection risk than airborne transmission. Under the baseline scenario of no surface cleaning and hand washing, the average fomite infection risk in all states is 0.48%. The states with high average airborne infection risk still ranked as the top states with the highest average fomite infection risk. Mitigation measures of hand cleaning and 50% remote study showed similar but poor results on reducing the fomite infection risk when being applied individually. Surface cleaning exhibit significant improvement in reducing fomite infection risk, which halved the average fomite infection risk solely. The combined control measures displayed small improvements in decreasing fomite infection risk when compared to the performance of surface cleaning. There was no obvious evidence to show that school level has an impact on the fomite infection risk under the baseline situation, but prekindergarten showed better improvement after applying the mitigation methods.

It is concluded that the Omicron spreads fast in U.S. schools, especially via airborne transmission. For instance, the average airborne infection risk is 4.51% without any mitigation measures, emphasizing the significance of mitigation measures to reduce the infection risks at lower level. Among the considered mitigation measures, the impact of implementing MERV 13 filtration indicated a significant improvement in reducing the airborne infection risk, and the overall average airborne infection risk was reduced to 1.55%. High schools are exposed to the highest airborne infection risk amongst all school levels. The impact of ventilation increase and partial online learning is similar, with the infection risk of 2.40% and 2.30%, respectively. The spread via fomite route was insignificant compared with airborne route, with an average infection risk of 0.48%. The transmission risk nearly the same for different school level. To further eliminate the fomite transmission, the most effective mitigation measure is surface cleaning, reducing the transmission infection risk to 0.22%.

ACKNOWLEDGEMENT

This research was funded by the National Science Foundation (NSF) via Grant 2026719 and the Joint Directed Research and Development Program of Science Alliance at the University of Tennessee Knoxville. The authors gratefully acknowledge the support from NSF and the Science Alliance. Any opinions, findings, conclusions, and recommendations expressed in this paper are those of the authors and do not necessarily reflect the views of NSF, The University of Tennessee, Knoxville, and The University of Texas at San Antonio.

REFERENCES

Azimi, P., and B. Stephens. 2013. "HVAC Filtration for Controlling Infectious Airborne Disease Transmission in Indoor Environments: Predicting Risk Reductions and Operational Costs." *Building and Environment* 70: 150–160.

Batterman, S., F. Su, A. Wald, F. Watkins, C. Godwin, and G. Thun. 2017. "Ventilation Rates in Recently Constructed U.S. School Classrooms." *Indoor Air* 27 (5): 880–890.

Bouwknegt, M., K. Verhaelen, A. Rzezutka, I. Kozyra, L. Maunula, C. H. Bonsdorff, A. Vantarakis, P. Kokkinos, T. Petrovic, S. Lazic, I. Pavlik, P. Vasickova, K. A. Willems, A. H. Havelaar, S. A. Rutjes, and A. M. R. Husman. 2015. "Quantitative Farm-to-Fork Risk Assessment Model for Norovirus and Hepatitis A Virus in European Leafy Green Vegetable and Berry Fruit Supply Chains." *International Journal of Food Microbiology* 198: 50–58.

Buonanno, G., L. Morawska, and L. Stabile. 2020. "Quantitative Assessment of the Risk of Airborne Transmission of SARS-CoV-2 Infection: Prospective and Retrospective Applications." *Environment International* 145: 106112.

CDC. 2022a. Omicron Variant: What You Need to Know. https://www.cdc.gov/coronavirus/2019-ncov/variants/omicron-variant.html, accessed 21th April.

CDC. 2022b. United States COVID-19 Community Levels by County. https://data.cdc.gov/Public-Health-Surveillance/United-States-COVID-19-Community-Levels-by-County/3nnm-4jni, accessed 21th April.

CDC. 2022c. CDC COVID Data Tracker: Variant Proportions. https://covid.cdc.gov/covid-data-tracker/#variant-proportions, accessed 21th April.

Cheng, V. C., D. C. Lung, S. Wong, A. K. Au, Q. Wang, H. Chen, L. Xin, A. W. Chu, J. D. Ip, W. Chan, H. Tsoi, H. Tse, K. H. Ng, M. Y. Kwan, S. Chuang, K. K. To, Y. Li, and K. Yuen. 2022. "Outbreak Investigation of Airborne Transmission of Omicron (B.1.1.529) - SARS-CoV-2 Variant of Concern in a Restaurant: Implication for Enhancement of Indoor Air Dilution." *Journal of Hazardous Materials* 430: 128504.

Conover, W. J., and R. L. Iman. 1981. "Rank Transformations as a Bridge Between Parametric and Nonparametric Statistics." *The American Statistician* 35 (3): 124–129.

Gammaitoni, L., and M. C. Nucci. 1997. "Using a Mathematical Model to Evaluate the Efficacy of TB Control Measures." *Emerging Infectious Diseases* 3 (3): 335–342.

Hota, B., B. Stein, M. Lin, A. Tomich, J. Segreti, and R. A. Weinstein. 2020. "Estimate of Airborne Transmission of SARS-CoV-2 Using Real Time Tracking of Health Care Workers." *MedRxiv*.

Hui, K. P.Y., J. C. W. Ho, M. Cheung, K. Ng, R. H. H. Ching, K. Lai, T. T. Kam, H. Gu, K. Sit, M. K. Y. Hsin, T. W. K. Au, L. L. M. Poon, M. Peiris, J. M. Nicholls, and M. C. W. Chan. 2022. "SARS-CoV-2 Omicron Variant Replication in Human Bronchus and Lung Ex Vivo." *Nature* 603 (7902): 715–720.

Jimenez, J., and Z. Cai. 2022. COVID-19 Aerosol Transmission Estimator. https://docs.google.com/spreadsheets/d/16K1OQkLD4BjgBdO8ePj6ytf-RpPMlJ6aXFg3PrIQBbQ/edit#gid=519189277, accessed 21th April.

NCES. 2008. Average Number of Hours in the School Day and Average Number of Days in the School Year for Public Schools. https://nces.ed.gov/surveys/sass/tables/sass0708_035_s1s.asp, accessed 21th April.

Klompas, M., and A. Karan. 2022. "Preventing SARS-CoV-2 Transmission in Health Care Settings in the Context of the Omicron Variant." *JAMA* 327 (7): 619–620.

Kraay, A. N.M., M. A.L. Hayashi, N. Hernandez-Ceron, I. H. Spicknall, M. C. Eisenberg, R. Meza, and J. N.S. Eisenberg. 2018. "Fomite-Mediated Transmission as a Sufficient Pathway: A Comparative Analysis across Three Viral Pathogens 11 Medical and Health Sciences 1117 Public Health and Health Services." *BMC Infectious Diseases* 18 (1): 1–13.

Kruskal, W. H., and W. A. Wallis. 1952. "Use of Ranks in One-Criterion Variance Analysis." *Journal of the American Statistical Association* 47 (260): 583–621.

Kwon, T., N. N. Gaudreault, and J. A. Richt. 2021. "Environmental Stability of SARS-CoV-2 on Different Types of Surfaces under Indoor and Seasonal Climate Conditions." *Pathogens* 10 (2): 227.

Li, S., Y. Xu, J. Cai, D. Hu, and Q. He. 2021. "Integrated Environment-Occupant-Pathogen Information Modeling to Assess and Communicate Room-Level Outbreak Risks of Infectious Diseases." *Building and Environment* 187:107394.

Lopez, G. U., C. P. Gerba, A. H. Tamimi, M. Kitajima, S. L. Maxwell, and J. B. Rose. 2013. "Transfer Efficiency of Bacteria and Viruses from Porous and Nonporous Fomites to Fingers under Different Relative Humidity Conditions." *Applied and Environmental Microbiology* 79 (18): 5728–5734.

Lyngse, F. P., C. T. Kirkeby, M. Denwood, L. E. Christiansen, K. Mølbak, C. H. Møller, R. L. Skov, T. G. Krause, M. Rasmussen, R. N. Sieber, T. B. Johannesen, T. Lillebaek, J. Fonager, A. Fomsgaard, F. T. Møller, M. Stegger, M. Overvad, K. Spiess, and L. H. Mortensen. 2022. "Transmission of SARS-CoV-2 Omicron VOC Subvariants BA.1 and BA.2: Evidence from Danish Households." *MedRxiv*.

Morawska, L., and J. Cao. 2020. "Airborne Transmission of SARS-CoV-2: The World Should Face the Reality." *Environment International* 139: 105730.

NCES. 2021. National center for education statistics (NCES). https://nces.ed.gov/ccd/elsi/tablegenerator.aspx, accessed 21th April.

Nicas, M., and D. Best. 2008. "A Study Quantifying the Hand-to-Face Contact Rate and Its Potential Application to Predicting Respiratory Tract Infection." *Journal of Occupational and Environmental Hygiene* 5 (6): 347–352.

Nicas, M., and R. M. Jones. 2009. "Relative Contributions of Four Exposure Pathways to Influenza Infection Risk." *Risk Analysis* 29 (9): 1292–1303.

Pitol, A. K., and T. R. Julian. 2021. "Community Transmission of SARS-CoV-2 by Surfaces: Risks and Risk Reduction Strategies." *Environmental Science and Technology Letters* 8 (3): 263–269.

Sobolik, J. S., E. T. Sajewski, L. Jaykus, D. K. Cooper, B. A. Lopman, A. N.M. Kraay, P. B. Ryan, J. L. Guest, A. Webb-Girard, and J. S. Leon. 2022. "Decontamination of SARS-CoV-2 from Cold-Chain Food Packaging Provides No Marginal Benefit in Risk Reduction to Food Workers." *Food Control* 136: 108845.

Standard 52.2- 2017 - American society of heating, refrigerating and air-conditioning engineers. https://ashrae.iwrapper.com/ASHRAE_PREVIEW_ONLY_STANDARDS/STD_52.2_2017, accessed 17th March.

WHO. 2020. Transmission of SARS-CoV-2: Implications for Infection Prevention Precautions. https://www.who.int/news-room/commentaries/detail/transmission-of-sars-cov-2-implications-for-infection-prevention-precautions, accessed 28th June.

WHO. 2021. Classification of Omicron (B.1.1.529): SARS-CoV-2 Variant of Concern. https://www.who.int/news/item/26-11-2021-classification-of-omicron-(b.1.1.529)-sars-cov-2-variant-of-concern, accessed 21th April.

Xu, Y., J. Cai, S. Li, Q. He, and S. Zhu. 2021. "Airborne Infection Risks of SARS-CoV-2 in U.S. Schools and Impacts of Different Intervention Strategies." *Sustainable Cities and Society* 74: 103188.

AUTHOR BIOGRAPHIES

YIFANG XU is a Ph.D. candidate and research assistant in the Department of Civil and Environmental Engineering at the University of Tennessee Knoxville. She earned her Master's degree at Carnegie Mellon University. Her research interests includes sensing, machine learning, data analytics, building information modeling, and simulation. Her email address is yxu79@vols.utk.edu.

SIYAO ZHU is a research assistant in the Department of Civil and Systems Engineering at Johns Hopkins University. He graduated from Carnegie Mellon University with a master's degree in Civil Engineering. His research of interest focuses on mathematic simulation and modeling, statistics, data analysis, natural language processing and web application design. His email address is szhu34@jhu.edu.

SHUAI LI is an Assistant Professor in the Department of Civil and Environmental Engineering at the University of Tennessee Knoxville. He graduated from Purdue University with a Ph.D. degree in Civil Engineering, a Master's degree in Industrial engineering, and a Master's degree in Economics. His research is centered on developing human-cyber-physical systems to improve built environment health and sustainability. His email address is sli48@utk.edu.

JIANNAN CAI is an Assistant Professor in the School of Civil & Environmental Engineering, and Construction Management at the University of Texas at San Antonio. She holds a Ph.D. degree in Civil Engineering from Purdue University and a M.S. degree in Civil Engineering from Tongji University. Her research interests include data sensing and analysis, computer vision, deep learning, and robotics in construction, infrastructure, and building engineering and management. Her e-mail address is jiannan.cai@utsa.edu.

QIANG HE is a Professor in the Department of Civil and Environmental Engineering at the University of Tennessee Knoxville. His research is centered on built environment microbiology and health. His email address is qianghe@utk.edu.