Influenza virus shedding and symptoms: Dynamics and implications from a multiseason household transmission study

Supplementary materials

Supplementary text

Specimen testing

Testing was performed at two sites: Marshfield Clinic Research Institute (MCRI) and Vanderbilt University Medical Center (VUMC). Both sites tested specimens using the CDC Human Influenza Virus Real-Time RT-PCR Diagnostic Panel and Influenza A/B Typing Kit. Forty-five cycles were performed for each reaction and, depending on the site, tests approaching negative or invalid results were typically repeated to ensure reproducibility. For the purpose of this analysis, we conservatively assumed that Ct values \geq 40 were negative. Following these procedures, we did not detect any systematic differences in Ct dynamics among the testing sites (Figure S1).

Model fitting in Monolix

We fit our models to the data using a nonlinear mixed-effects (NLME) framework in Monolix 2021R2. Monolix is used extensively in the fields of within-host modeling and pharmokinetics / pharmacodynamics and is available at https://lixoft.com/products/monolix/. We fit $\hat{V}(t)$ to the Ct observations, treating negative Ct tests as censored observations, and fit $W(t)$ to the symptom score data. We assumed normal distribution of both variables with constant error terms and ensured model residuals were normally distributed using the Shapiro-Wilk test. Each parameter was allowed to vary across individuals by including both a fixed and random effect. We assumed a, b and h were lognormally distributed to ensure positivity, and d was normally distributed to allow positive or negative shifts in time. We found no strong evidence for correlations between parameters during initial model fitting and so assumed all parameters were independent in subsequent fitting. We explored models that controlled for candidate covariates (age group, vaccination status, virus type or season) with respect to one or more parameters and evaluated the importance of each covariate-parameter relationship using ANOVA. Relationships with p-values < 0.01 were kept in the final model. We compared models assuming different distributions for f_v and f_w (Weibull, gamma, or lognormal) using Akaike Information Criterion (AIC), where $AIC = 2k - 2lnL$, k is the number of estimated parameters, and $ln L$ is the maximum log likelihood.

Calculating trajectory summary metrics

For each fitted Ct trajectory, $\hat{V}(t)$, we estimated the onset (clearance) of shedding as the first (last) time at which $\hat{V}(t) \geq 1$. The duration of shedding was the time between these two estimates. Since these estimates vary based on the choice of threshold (here equal to 1), they are most useful in making relative comparisons between covariate groups, rather than determining absolute values.

Similarly, for each fitted symptom score trajectory $(W(t))$, the time of symptom clearance was estimated as the last time at which $W(t) \geq 0.3$. The threshold of 0.3 was used as the data are not continuous, and a score of 0.3 equals the reporting of one symptom (out of runny nose, nasal congestion, or fatigue) for S_{ANY} . We do not need to calculate an onset time for the symptom score trajectories as they are already estimated relative to time since symptom onset.

Hierarchical partitioning

Intuition

To distinguish the covariates with the greatest independent influence on trajectory dynamics from those acting primarily through collinearity with other variables, we performed hierarchical partitioning on the summary metrics. For each covariate, hierarchical partitioning considers all possible nested models within the full multivariate regression model derived from that covariate, then assesses the average increase in goodness-of-fit (∆GoF) achieved by including the covariate in each model. For example, to assess the influence of covariate A in a multivariate linear regression including covariates A, B, and C, one would consider the nested hierarchies (A, AB, ABC) and (A, AC, ABC), where AB indicates the sub-model with A and B as covariates, and so on. One would then calculate the Δ GoF from including A in each model and take the average. This approach ensures the sum of the average influences of each covariate is equal to the total ∆GoF between the full and null models. Thus, the average influences form a partition of the combined explanatory power of all covariates, and the percentage importance of each covariate is its average ∆GoF over the total ∆GoF multiplied by 100. One advantage of this approach is that the percentage importance returned for each covariate reflects its independent influence on the dependent variable, having averaged out effects of collinearity with other covariates. Furthermore, by considering all possible models within each hierarchy, the approach is not sensitive to the order in which models are assessed, as can be the case with other algorithms.

Example

Here we outline the hierarchical partitioning approach for a regression model with three independent variables, taken from Chevan & Sutherland (1991). Consider a multivariate linear regression model with dependent variable Y and independent variables A, B and C. Let M_{ij} denote the model including i and j, for $i, j \in (A, B, C)$, and let X_{ij} denote the corresponding goodness-of-fit value (GoF). Similarly, let M_{ABC} denote the full regression model and M_0 the null model, and X_{ABC} , X_0 the corresponding GoFs, respectively.

First consider all the nested hierarchies within the full regression model, M_{ABC} , and their corresponding GoFs. Ignoring the null model, we can list these hierarchies as follows:

	Hierarchy 1 Hierarchy 2 Hierarchy 3 Hierarchy 4 Hierarchy 5 Hierarchy 6				
$\rm (H_{A1})$	(H_{A2})	$\rm(H_{B1})$	$\rm(H_{B2})$	$\rm(H_{C1})$	$\rm(H_{C2})$
X_A	X_A	$X_{\rm B}$	$X_{\rm B}$	X_{C}	X_{C}
X_{AB}	$\rm X_{AC}$	X_{AB}	X_{BC}	X_{AC}	$X_{\rm BC}$
X_{ABC}	X_{ABC}	X_{ABC}	X_{ABC}	X_{ABC}	X_{ABC}

We can see that hierarchies H_{A1} and H_{A2} represent subsets in which all models include the variable A, H_{B1} and H_{B2} are subsets in which all models include B, and H_{C1} and H_{C2} are subsets in which all models include C. Thus we refer to A as the principle variable for hierarchies H_{A1} and H_{A2} , B the principal variable for H_{B1} and H_{B2}, and so on. For each model, then consider the increase in GoF (Δ GoF) obtained by including the principle variable. These differences can be expressed as

Let S_{A1} denote the sum of the ΔG oFs for hierarchy H_{A1}, S_{A2} the sum of the ΔG oFs for hierarchy H_{A2} , and so on. Then

$$
S_{\text{A1}} = (X_{\text{A}} - X_0) + (X_{\text{AB}} - X_{\text{B}}) + (X_{\text{ABC}} - X_{\text{BC}})
$$

$$
S_{\text{A2}} = (X_{\text{A}} - X_0) + (X_{\text{AC}} - X_{\text{C}}) + (X_{\text{ABC}} - X_{\text{BC}}).
$$

Similar expressions can be written for S_{B1} , S_{B2} , S_{C1} and S_{C2} .

The average ΔG oF for all nested hierarchies in which A is the principle variable, D_A , is then given by

$$
D_{\rm A} = \frac{S_{\rm A1} + S_{\rm A2}}{6}
$$

=
$$
\frac{(X_{\rm A} - X_0) + (X_{\rm AB} - X_{\rm B}) + (X_{\rm ABC} - X_{\rm BC}) + (X_{\rm A} - X_0) + (X_{\rm AC} - X_{\rm C}) + (X_{\rm ABC} - X_{\rm BC})}{6}
$$

=
$$
\frac{2X_{\rm ABC} + X_{\rm AB} + X_{\rm AC} - 2X_{\rm BC} - X_{\rm B} - X_{\rm C} + 2X_{\rm A} - 2X_0}{6}.
$$

It follows that if we sum the average ∆GoFs across all variable hierarchies we get

$$
D_{A} + D_{B} + D_{C} = \frac{S_{A1} + S_{A2} + S_{B1} + S_{B2} + S_{C1} + S_{C2}}{6}
$$

$$
= \frac{6X_{ABC} - 6X_{0}}{6}
$$

$$
= X_{ABC} - X_{0}.
$$

In other words, the sum of the average ∆GoFs for each variable is equal to the total ∆GoF between the full and null models. Thus the average ΔG GoFs (D_A, D_B and D_C) partition the combined explanatory power of the full model among each of the independent variables, A, B and C.

Identifying fever from S_{ILI}

The fitted S_{ILI} trajectories are a continuous representation of a discrete scoring system and so although fever is assigned a value of 3 in S_{ILI} , anything greater than 2 (i.e. anything above the score assigned for cough + sore throat) is interpreted as possible fever. Instances where the fitted S_{ILI} trajectory for an individual who did not report fever attained a value greater than 2 were relatively rare (6/68 fitted trajectories; 9%). Similarly, just $1/63$ (2%) individuals who reported fever had an S_{ILI} trajectory that did not attain a value greater than 2. Thus the $S_{ILI} > 2$ threshold is a faithful means of identifying occurrences of fever from fitted ILI symptom score data.

Supplementary tables

Table S1 - Initial conditions for nonlinear mixed-effects model fitting in Monolix. All other parameters were set to default values. Abbreviations: ILI = influenza-like illness.

Covariate	Number $(\%)$	
Age (years)		
5	22(19)	
$5 - 17$	41(35)	
18-49	39 (34)	
>50	14(12)	
Current season influenza vaccination status		
Not vaccinated	68 (59)	
Vaccinated	48(41)	
Virus type		
Influenza A	86 (74)	
Influenza B	30(26)	
Symptoms		
Reported any ILI symptom	105(91)	
Reported any other symptom without ILI	3(2)	
Reported no symptoms (asymptomatic)	8(7)	

Table S2 – Characteristics of household contacts infected with influenza viruses included in analysis ($N = 116$).

Table S3 – Individual breakdown by age and influenza vaccination status or ILI symptom reporting ($N = 116$).

Age (years)	Current season vaccination status	Number $(\%)$	Reported any ILI symptom	Number $(\%)$
5	No	11(9)	N _o	2(2)
${<}5\,$	Yes	11(9)	Yes	20(17)
$5 - 17$	$\rm No$	27(23)	N _o	5(4)
$5 - 17$	Yes	14(12)	Yes	36(31)
18-49	No	25(22)	N _o	3(3)
18-49	Yes	14(12)	Yes	36(31)
≥ 50	$\rm No$	5(4)	N _o	1(1)
≥ 50	Yes	9(8)	Yes	13(11)

Table S4 – AIC comparison of model fits to 105 trajectories relative to ILI symptom onset. The difference in AIC, ∆AIC, for model i is calculated as the difference in AIC value between model i and the best-fitting model with the lowest AIC. Thus, Δ AIC = 0 for the best-fitting model. A difference greater than 2 between two models suggests greater statistical support for the model with lower AIC.

	Distribution \vert ΔAIC , Ct model [*]	ΔAIC , S_{ILI} model**
Weibull		
gamma	71.1	17.1
lognormal	72.8	375

[∗]Shape and magnitude parameters modified by age.

∗∗Scale parameter modified by age and magnitude parameter modified by vaccination status.

Table S5 – AIC comparison of model fits to 108 trajectories relative to any symptom onset. The difference in AIC, ∆AIC, for model i is calculated as the difference in AIC value between model i and the best-fitting model with the lowest AIC. Thus, $\Delta AIC = 0$ for the best-fitting model. A difference greater than 2 between two models suggests greater statistical support for the model with lower AIC.

		Distribution ΔAIC , Ct model [*] ΔAIC , S_{ANY} model ^{**} ΔAIC , S_{UNW} model ^{**}	
Weibull			
gamma	2.7	17.6	15.5
lognormal	4.4	22.8	25.2

[∗]Shape and magnitude parameters modified by age.

∗∗Scale parameter modified by age and magnitude parameter modified by vaccination status.

Age group	Vaccination status	Season	Virus type
$<$ 5	${\rm Yes}$	2019-2020	Infuenza B
$<$ 5	No	2019-2020	Infuenza A
5	No	2019-2020	Infuenza A
$5 - 17$	Yes	2017-2018	Influenza A
$5 - 17$	No	2018-2019	Influenza A
$5 - 17$	No	2018-2019	Influenza A
$5 - 17$	Yes	2018-2019	Influenza A
$5 - 17$	Yes	2018-2019	Influenza A
$5 - 17$	N _o	2018-2019	Influenza A
18-49	Yes	2018-2019	Influenza A
18-49	Yes	2018-2019	Influenza A
18-49	No	2019-2020	Influenza A
18-49	No	2019-2020	Influenza B
18-49	No	2019-2020	Influenza B
≥ 50	Yes	2017-2018	Influenza A
≥ 50	No	2018-2019	Influenza A

Table S6 – Characteristics of 16 participants with presymptomatic shedding estimated to be more than 50% of total shedding.

Supplementary figures

Figure S1 - Ct values by site, age group and season. Columns are different seasons (left to right: 2017-2018, 2018-2019, 2019-2020) and rows are different age groups (top to bottom: less than 5 years, 5-17 years, 18-49 years, and 50 years and older). Abbreviations: ILI = influenza-like illness; MCRI = Marshfield Clinical Research Institute; VUMC = Vanderbilt University Medical Center.

Figure S2 - Inclusion and exclusion of individuals. Incident infection refers to infected individuals who had a recorded negative test before their first positive test. Abbreviations: $|LI|$ = influenza-like illness.

Figure S3 – Fitted individual virus shedding trajectories relative to day of ILI symptom onset ($N = 105$). The best-fit model was a Weibull distribution with shape and magnitude parameters modified by age.

Figure S4 – Fitted individual S_{ILI} trajectories relative to day of ILI symptom onset (N = 105). The best-fit model was a Weibull distribution with scale parameter modified by age and magnitude parameter modified by vaccination status.

Figure S5 – Best-fit parameters. Parameter estimates from the best-fitting models for (A) Virus shedding relative to ILI onset; (B) Virus shedding relative to any symptom onset; (C) S_{ILI} scores; (D) S_{ANY} scores; and (E) S_{UNW} scores. Colors show parameters that were modified by age or vaccination status.

Figure S6 – Fitted individual virus shedding trajectories relative to day of any symptom onset $(N = 108)$. The best-fit model was a Weibull distribution with shape and magnitude parameters modified by age.

Figure S7 – Fitted individual S_{ANY} trajectories relative to day of any symptom onset (N = 108). The best-fit model was a Weibull distribution with scale parameter modified by age and magnitude parameter modified by vaccination status.

Figure S8 – Fitted individual S_{UNW} trajectories relative to day of any symptom onset (N = 108). The best-fit model was a Weibull distribution with scale parameter modified by age and magnitude parameter modified by vaccination status.

Figure S9 - Associations between virus shedding and age for individuals experiencing any symptoms. Summary metrics shown in the top panels from left to right are: day of shedding clearance relative to day of any symptom onset; day of shedding onset relative to any symptom onset; day of peak shedding relative to day of any symptom onset. Bottom panels from left to right: duration of shedding in days; peak value of shedding attained (transformed as 40 – Ct); and total virus shed, as measured by the area under the fitted shedding curve (AUC). $^*p < 0.05, \; ^{**}p < 0.01, \; ^{***}p < 0.001, \; ^{***}p < 0.0001.$

Figure S10 - Children under 5 have higher peak ILI scores and shorter ILI symptom durations. Summary metrics shown in the top panels from left to right are: day of ILI symptom clearance relative to day of ILI onset; day of peak ILI score relative to day of ILI onset; duration of ILI symptoms in days. Bottom panels from left to right: peak ILI score; total ILI score, as measured by the area under the fitted ILI symptom curve (AUC); proportion of individuals in each age group experiencing fever (as estimated by a fitted ILI score >2). $*_p$ < 0.05, $*_p$ < 0.01, $**_p$ < 0.001, $***_p$ < 0.0001.

Figure S11 – $S_{\rm ANY}$ removes the association between peak symptom score and age. Summary metrics shown in the top panels from left to right are: day of symptom clearance relative to day of any symptom onset; day of peak score relative to day of onset; duration of symptoms in days. Bottom panels from left to right: peak score; total score, as measured by the area under the fitted symptom curve (AUC); proportion of individuals in each age group experiencing fever or LRT (as estimated by a fitted score >3). LRT represents symptoms associated with lower respiratory tract infection (i.e., wheezing or shortness of breath). $*_p$ < 0.05, $**_p$ < 0.01, $***_p$ < 0.001, $****p<0.0001.$

Figure S12 – S_{UNW} removes the association between peak symptom score and age. Summary metrics shown in the top panels from left to right are: day of symptom clearance relative to day of any symptom onset; day of peak score relative to day of onset; duration of symptoms in days. Bottom panels from left to right: peak score; total score, as measured by the area under the fitted symptom curve (AUC). *p < 0.05, ${}^{**}p$ < 0.01, ${}^{***}p$ < 0.001, ${}^{***}p$ < 0.0001.

Figure S13 – No detected associations between virus shedding and current season vaccination status. Summary metrics shown in the top panels from left to right are: day of shedding clearance relative to day of ILI symptom onset; day of shedding onset relative to ILI onset; day of peak shedding relative to day of ILI onset. Bottom panels from left to right: duration of shedding in days; peak value of shedding attained (transformed as 40 – Ct); and total virus shed, as measured by the area under the fitted shedding curve (AUC). $*_p$ < 0.05, $*_p$ < 0.01, $**_p$ < 0.001, $***_p$ < 0.0001.

Figure S14 – Tests of independent covariate contributions using hierarchical partitioning. Associations between covariates and select summary metrics for virus shedding (A) or ILI symptom scores (B). The day of peak is relative to days since ILI symptom onset. Abbreviations: AUC = area under the curve; ns = not significant. $*_p$ < 0.05, $*_p$ < 0.01, $***_p$ < 0.001, $***_p$ < 0.0001.

Figure S15 – Vaccinated individuals experience reduced duration of unweighted symptom scores and reduced total unweighted symptom scores. Panels from left to right are: day of peak score relative to day of any symptom onset; duration of symptoms in days; peak score; total score, as measured by the area under the fitted symptom curve (AUC). $*_p$ < 0.05, $**_p$ < 0.01, $***_p$ < 0.001, $****p < 0.0001$.

Figure S16 - No association between vaccination status and $S_{\rm ANY}$. Panels from left to right are: day of peak score relative to day of any symptom onset; duration of symptoms in days; peak score; total score, as measured by the area under the fitted symptom curve (AUC). *p < 0.05, ${}^{**}p$ < 0.01, ${}^{***}p$ < 0.001, ${}^{***}p$ < 0.0001.

Figure S17 – Additional associations between virus shedding and season (A) or symptom severity category (B). Shown are associations with day of shedding onset (left); day of peak shedding (middle); and total virus shed (right). Individuals with peak ILI scores > 2 are classified as experiencing 'moderate' symptoms; all others are classified as experiencing 'mild' symptoms. Days represent days since ILI symptom onset and AUC represents the area under the curve. $*_P< 0.05,$ $*_P< 0.01,$ $^{***}_P< 0.001,$ $^{***}_P< 0.0001.$

Figure S18 – Fitted individual virus shedding trajectories relative to day of first positive test. Fits for asymptomatic (A) and symptomatic (B) individuals with incident infection from the best-fitting Weibull distribution. Model parameters were not modified by any covariates; age group is shown for reference only.

Figure S19 – Summary metrics for asymptomatic and symptomatic individuals with incident infection. Shown are: (A) day of peak shedding relative to day of first positive test; (B) duration of shedding in days; (C) Peak value of shedding attained (transformed as 40 – Ct); and (D) total virus shed, as measured by the area under the fitted shedding curve (AUC).

Figure S20 – Duration-based isolation strategies may be effective in reducing shedding after isolation from symptomatic individuals but could require individuals to isolate for longer. Estimates of shedding remaining (A) and duration of isolation in days (B) for different possible isolation strategies. A combined fever- or duration-based strategy indicates that individuals with fever isolate until 24 hours after fever resolution and individuals without fever isolate for three, five, or seven days after ILI symptom onset. A solely-duration based strategy indicates that all individuals isolate for three, five, or seven days after ILI symptom onset, regardless of whether they experience fever or not. Points represent the median and error bars are the 90th percentiles.