HPAI virus transmission is shaped by inter-specific social network structure.

Jamie Dunning[1], Anna Gamża[2], Josh Firth[1,3], Adham Ashton-Butt[4,5], Rowland Kao[2,6],

Ian Brown[7,8] and Alastair I. Ward[1].

[1]Faculty of Biological Sciences, University of Leeds, Leeds, United Kingdom

[2]The Roslin Institute, University of Edinburgh, Edinburgh, United Kingdom

[3]Department of Biology, University of Oxford, Oxford, United Kingdom

[4]British Trust for Ornithology, Thetford, United Kingdom

[5]School of Environmental Sciences, University of East Anglia, Norwich, UK

[6]School of Physics and Astronomy, University of Edinburgh, Edinburgh, United Kingdom

[7]International Reference Laboratory for Avian Influenza, Animal and Plant Health
Agency (APHA-Weybridge), Addlestone, United Kingdom

[8]The Pirbright Institute, Pirbright, United Kingdom

*Corresponding author: j.dunning@leeds.ac.uk

Abstract: The emergence of zoonotic and epizootic disease from communities of
wild animals is a recurrent threat to human and animal health, to food and economic
security. This is particularly true for disease systems that involve many interacting
species, where the varied ecological and behavioural diversity of those species interact,
driving complex pathways of transmission, and where sampling many species across
time and space is difficult. As a consequence, surveillance of disease across
communities of wild animals is largely reliant on responsive, rather than preventative,
sampling after an outbreak event. Here, we inferred social networks of wild birds using
five years of bird survey data from a county in Northern England. We mapped 8,162
links between 159 species, and combined this with Highly Pathogenic Avian Influenza
virus (HPAIV) genomic similarity measures from 35 host species, measured over 388
sequences. Inter-specific social network position predicted similarity between viral
genomes, consistent with HPAIV transmission between species that co-occur in the
wild. Our results have important applications for surveillance and prioritization of
zoonotic and epizootic disease, and provide an empirical basis for future theoretical and
species trait-based evaluation of pathogen spread among ecological communities.

Introduction: The repeated emergence of zoonotic and epizootic diseases of
pandemic potential from communities of wild animals is a recurrent threat to human and
animal health (Kruse, Kirkemo, and Handeland 2004; Kuiken et al. 2005; Karesh et
al. 2012; Holmes 2022; World Health Organization 2024), with far-reaching
consequences for global economic and food security (Clemmons, Alfson, and Dutton III
2021; Bernstein et al. 2022). For example, Avian Influenza viruses (AIVs), SARS-CoV-
2, Ebola virus, Herpes viruses, Marburg virus, MERS-CoV and West Nile virus all
originate from communities of wild animals with little detection prior to outbreaks in
humans or livestock (Jones et al 2008; Carlson et al. 2022). However, in (non-human)
animal communities, patterns of disease transmission are highly variable, and cannot
be solely explained by pathogen virulence. Instead, just as human mobility and
interaction shapes the trajectory of an epidemic, (Firth et al. 2020; Kraemer et al. 2020;
Kostandova et al. 2024, 2025), animal social network structure, shaped by host ecology
and the social and physical environment, must also influence disease propagation
through communities of wild animals.

Wild animal social systems, involving many interacting individuals, are complex and
dynamic, shaped by the demography and varied behavioural preferences of their
constituents (Kulahci and Quinn 2019; Albery et al. 2022; Beck, Sheldon, and Firth
2023; Dunning et al. 2023; Schroeder et al. 2024), and the physical and social
environments within which they exist (Firth, Sheldon, and Farine 2016; Firth, Sheldon,
and Brent 2017; Motes-Rodrigo et al. 2025). This complexity is magnified in inter-
specific, or multi-host systems, where many species with a broad diversity of behavioral
traits and spatial preferences, interact (Bansal, Grenfell, and Meyers 2007;
Buhnerkempe et al. 2015; Sah et al. 2017; Sah, Mann, and Bansal 2018; Farine,
Garroway and Sheldon 2020; Hillemann et al. 2020; Collier et al. 2022). It is this
inherent complexity that drives network structure and, in the context of non-vector-borne
disease, provides the network links through which disease may spread (Bansal,
Grenfell, and Meyers 2007; Wolinska and King 2009; Sah, Mann, and Bansal 2018;
King, Hall, and Wolinska 2023; Prosser et al. 2023). For example, during the H5N1
2.3.4.4b highly pathogenic avian influenza (HPAI) outbreak that affected seabirds in
Western Europe in the summer of 2021, the presence of disease in otherwise isolated

nesting colonies of Northern Gannet *Morus bassanus* prompted a short-term increase in

between-colony connectivity, as birds abandoned infected breeding sites, shaping the

structure of the social network and driving further spread through seabirds (Jeglinski et

al. 2024). This host expansion had devastating consequences for the conservation of

affected wild birds (Banyard et al. 2022; Falchieri et al. 2022; Pohlmann et al. 2023;

Macgregor et al. 2024; Tremlett et al. 2025), but also drove HPAI spread into new

continents (Letsholo et al. 2022; Stokstad 2022; Kandeil et al. 2023; Andrew et al. 2024;

Bennison et al. 2024) and novel systems like domestic and wild mammals (Burrough et

al. 2024; Plaza et al. 2024; Sah et al. 2024; Uhart et al. 2024) including humans (Li et

al. 2019; Sidik 2023).

It is perhaps because of this complexity, that research into animal disease systems has

tended to focus on the role of specific traits (Garamszegi and Møller 2007; Luis et

al. 2015; Tian et al. 2015; Olival et al. 2017; Albery et al. 2020, 2021; Pearce-Higgins et

al. 2023; Yin et al. 2023; Vickers et al. 2024) and/or environmental components

(Keesing et al. 2010; Carlson et al. 2022; King, Hall, and Wolinska 2023; Prosser et

al. 2023; Desvars-Larrive et al. 2024), rather than the structure of the global social

system. However, most traits (e.g. shared habitat, dietary preference, or migratory

phenology) and environmental conditions influence transmission by shaping community

network structures – forcing potential hosts together or driving them apart. This spatial

and temporal clustering either facilitates or constrains pathogen transmission through

social links

Understanding first the pattern of disease spread through multi-host networks, and then

the traits and conditions that shape those networks, are both important knowledge gaps

to informing preventative surveillance and prioritization of zoonotic and epizootic

disease systems (Luis et al. 2015; Marí Saéz et al. 2015; Olival et al. 2017; Bonneaud

and Longdon 2020, Desvars-Larrive et al. 2024; Webby and Uyeki 2024). Both have

been challenging to test empirically and perhaps as a consequence evaluation of multi-

host network disease dynamics has been reliant on theoretical models (Sah et al. 2017;

Albery et al. 2020, 2021; McDuie et al. 2024; Ryding, Ross, and Klaassen 2025). There

is therefore a pressing need for new predictive approaches to identify the species and

pathways that drive zoonotic and epizootic disease spread, in order to inform risk-based

policy interventions. To test the hypothesis that social proximity in multi-species

networks of wild animals predicts disease transmission, something that although is often

assumed, has been very difficult to demonstrate in a wild system, we evaluated the

relationship between wetland bird community structure and genomic relatedness

between highly pathogenic avian influenza (HPAI) viruses sampled from species found

in those communities. HPAIs represent a disease system with a broad geographic and

host taxonomic span (Lupiani and Reddy 2009; Klaassen and Wille 2023; Webby and

Uyeki 2024) with recurrent diseases of wildfowl and waterbirds wildfowl (Pohlmann et

al. 2022; Atkinson and Baillie 2024) and frequent incursion into poultry (Lupiani and

Reddy 2009; Lycett, Duchatel, and Digard 2019; Gao 2014; Blagodatski et al. 2021).

Recent access to large repositories of citizen-science data on wild animal distributions

(Sullivan et al. 2009; Albery et al. 2020; Macgregor et al. 2024; Vickers et al. 2024),

alongside sampling and sequencing of viruses circulating within these communities

(Byrne et al. 2023; Gamża et al. 2024) now provides an opportunity to study the effect

of social network structure on the spread of zoonotic and epizootic disease in wild

animals. To demonstrate this, we used HPAI as a study system - HPAI represents a

serious threat to public health (World Health Organization 2024; UK Health Security

Agency 2025), with trans-boundary transmission between hundreds of interacting hosts

(Klaassen and Wille 2023), and via multiple channels of transmission (Malik et al. 2021;

Sun et al. 2018; Reid et al. 2024). But, up to now, access to host ecology data and

sampling for HPAI in the environment have been major constraints to landscape-scale

predictive modelling (Kruse, Kirkemo, and Handeland 2004; Kuiken et al. 2005),

Although several studies have described inter-specific HPAI transmission within

communities of wild birds (Boulinier 2023; Coffey and Verspoor 2025), and in some

cases in response to disease within the network (Jeglinski et al. 2024; but also see

Teitelbaum et al. 2023), or aligned phenology of wild bird behaviours with outbreaks in

poultry (Tian et al. 2015; Vickers et al. 2024; Gamża et al. 2024; Shemmings-Payne et

al. 2024), at present, HPAI surveillance, and predictive modelling, is limited by reactive

(i.e. *post* disease emergence) virus sample collection and processing availability, and

taxonomic biases in existing sampling data (Wade et al. 2022; Atkinson et al. 2025, but

also see, Wannigama et al. 2025). Social networks have been applied to simpler, direct

transmission (Côté and Poulinb 1995; Gómez, Nunn, and Verdú 2013), and single

species systems (Wilson-Aggarwal et al. 2019; Proboste et al. 2024), including humans

(Klovdahl 1985; Firth et al. 2020), but not yet in complex transmission systems of wild

animals.

We combined social network analysis with a viral phylodynamic and Bayesian

generalized (non-)linear multilevel models to test the relationship between co-

occurrence of wild birds in the landscape and genetic distance between HPAI viral

genomes. We predict that social links will correlate with HPAI viral genome similarity, a

proxy for transmission, in a multi-species network of wild birds, at the landscape scale.

Methods: To test the hypothesis that social proximity predicts more similar virial

genetic distances across multi-species networks of wild birds, we combined social

network analysis with phylodynamic and Bayesian mixed modelling approaches. We

tested if our results differed from the expected network, without social structure, by

running a series of permutations that mirrored our observed data models.

Survey effort and Networks: To build species co-occurrence networks, we accessed

five years of data from the British Trust for Ornithology Wetland Bird Survey (WeBS),

2018 - 2022 for two overlapping regions of East Yorkshire, UK, each defined by a 50km

circular buffer around two recurrent HPAI outbreak sites. Each year represented a

number of sampling events (surveys) within the non-breeding season (October to

March; for more information of WeBS survey methods, see Woodward et al. 2024).

From these networks we extracted two established dyadic (pairwise - between two

species) measures of association from our social networks. To measure the extent to

which two species co-occur in the landscape, and therefore, may be expected to share

virus more easily, we used pairwise edge weight, the absolute frequency of co-

occurrence in the network; Then, to capture the extent to which a species pair are

associated in space and time, accounting for absolute co-occurrence relative to the

opportunity for co-occurrence, we also used the Simple Ratio Index (SRI; see Farine

and Whitehead 2015), that measures between 0 (no over-lap between a species) and 1

(where one species is recorded so is the other, without exception). Although both

measure interaction between species, pairwise weight and SRI represent different

aspects of interaction in the landscape. Where pairwise weight is the absolute

frequency of co-occurrence and a high value denotes stronger co-occurrence in the

landscape, a higher SRI value represents stronger relative association, regardless of

abundance. For example, in our WeBS data, the highest SRI are between relatively

scarce species that share a habitat niche, for example Dipper *Cinclus cinclus* and Grey

Wagtail *Motacilla cinerea* that both favor fast flowing upland streams. Although they are

both rare in the landscape, they are almost always recorded at the same sites. Finally,

we restricted the network used in our models to only include the species also present in

the viral phylodynamic study (see below), while weights and SRI measures were

calculated and carried over from the global social network.

Network similarity: We tested the assumption that out networks are comparable

between years, that is that the dyads that make up the general network structure were

similar across our five years of data collection. We did this using two measures

designed to compare non-uniform networks, in this case, with variation in the species

recorded -the network actors (nodes)- between years: 1) Jaccard similarity describes

the proportion of shared dyads between two networks, regardless of weight; and, 2) a

Spearman rank correlation test to measure similarity of dyadic edge weights between

species pairs present in both networks. In both cases 1 denotes identical network

structure, and 0 denotes no relationship.

Viral genetic similarity: We accessed 715 viral full genome sequences of H5N1

viruses collected in Great Britain, initially from 59 host species from the Global Initiative

on Sharing All Influenza Data (GISAID), a global repository including Influenza genome

data. To define genetic distance between viral genome sequences, we classified them

by reassortment profile (see Gamża et al. 2024). We aligned the sequences using

MAFFT v7.511 (Katoh and Standley 2013), trimmed them to coding regions, removed

insertions present in fewer than 10% of sequences and rejected sequences with

nucleotide coverage lower than 80% for all segments. We identified clusters for each of

the eight gene segments using nearest-neighbor hierarchical clustering of nucleotide

distances in the bioseq package in R (Keck and Mahon 2020; R Core Team 2023). We

used a 0.5% distance threshold for the Polymerase Basic (PB)1, PB2, and Polymerase

Acidic gene segments, and 1% for all others. We aligned each sequence with host

information, after filtering out mammals, domestic birds and taxonomically vague entries

(none of which are recorded as part of WeBS surveys), as well as non- H5N1 strains

(H5N5 and H5N8). We recorded the date associated with each sampling event and a

location, provided by the Animal and Plant Health Agency (APHA). We compared each

sequence with all others in the database to quantify a genetic distance between

pairwise viral genomes using the Tamura and Nei 1993 model (Tamura & Nei, 1993)

using the APE package for R (Emmanuel Paradis, 2024)) that calculates genetic

distance as a proportion that differ between each pair of sequence, accounting for
difference in rates for both kinds of transition and transversion., as well as measures of
geometric (space between sampling events) and temporal (time between sampling
events) distance. For more details on how these data were generated see Gamża et
al. (2024). Finally, we further filtered these data to only include species pairs also
present in at least one of our five social networks, leaving 763 pairwise samples
between 19 wild host species.

Data structure: To test our predictions that high between-species co-occurrence, or
greater association between a species pair, should result in a greater chance of viral
transmission, we built and extracted edge-based centrality metrics from five years of
BTO WeBS data and modeled these against similarity of host viral genomes (genetic
distance). We used smaller genetic distance (more similar) between viral sequences as
a proxy for transmission, yet, because there are relatively few viral samples taken from
relatively few wild bird hosts (relative to the number in the social networks) our models
only contained species present in both data-sets. We used the maximum genetic
distance between host samples as the response variables, and controlled for the space
and time-elapsed between sampling as well as the contribution of species within our
dyads as individuals in our fixed effects, in all of our models.

Model fit: To test the relationship between wild bird social network structure and
genetic distance between HPAI viruses, and to accommodate multi-membership
sampling in our species dyads, we ran a series of Generalized Linear Mixed Models
(GLMMs) using Bayesian Markov Chain Monte Carlo (MCMC) simulations with the
Hamiltonian Monte Carlo (HMC) and No-U-Turn Sampler (NUTS) algorithms in the brms
package (Bürkner 2017). All models used the maximum genetic distance (least similar)
between pairwise viral genomes, a conservative proxy for transmission between hosts,
as the response variable. Otherwise, our models only differed only by the first predictor
(fixed effect) variable, which was either pairwise weight or SRI. For all models, we used
weakly informative priors, and ran each over 4 chains of 4,000 iterations, with a warm-
up of 1,000 iterations and a thinning interval of 1. We used Effective Sample Sizes
(ESS) of >5000 in the posterior and tail distributions to maintain sampling efficiency and

a scale reduction factor (Ř) values of 1 to ensure convergence. We also manually

checked posterior trace plots to ensure model mixing. The fixed effects were considered

statistically significant when the 95% credible interval (CI) excluded zero.

Pairwise weight: We modeled pairwise weight, the mean of geometric distance

between viral pairwise sample locations and the mean of pairwise temporal distance

(time elapsed between sampling events) as fixed effects. We z-transformed all fixed

effects to better align scales between other variables in the model. We used the mean

(rather than the max) of geometric- and temporal distance to account for wide variation

in sampling and to reduce marginal collinearity. Because most species appeared across

many dyads, we accounted for species specific effects on genetic distance

independently of their dyad (i.e. species A + species B, rather than speciesAB) by

including species A and species B as a linked 'multi-membership' variable inside our

random effects. This approach also avoided over-dispersion.

SRI: We repeated the first model, using the same model structure but with SRI, instead

of pairwise weight, as a fixed effect. We used the log-odds (using a logit link function) of

SRI to better accommodate a linear relationship between SRI and other predictors in

the model.

Permutations: In order to test that our results differed from the expected distribution

without social structure in the network, we repeated our models with a series of network

permutations. We did this by 're-wiring' the observed network, shuffling the edges

between species pairs while maintaining the degree distribution for each species node

(Csardi and Nepusz 2006). We rewired networks 1000 times within years, before

combining them into a global network within each permutation cycle. Edges were

rewired between species nodes, breaking the community structure of the observed

network, but, because some species are much more frequent in our data -and therefore

our networks have some strong ties- we sampled edges from the empirical distribution

of edge weights (Farine 2017). This controlled for the chance that some effects are the

result of some species having more interactions over all, rather than who those

interactions were with. We maintained the structure of our original models, but because

we were only interested in effect sizes we reduced the number of iterations and the

warm up by half (from 4000 to 2000, and 1000 to 500, respectively) and ran the

permutation over 100 cycles. We inferred significance, that the effect of social structure

on genetic distance in our observed models was stronger than expected under a system

of random mixing, where our observed credible intervals fell outside of the 95%

confidence intervals of the permuted estimate.

Results:

Data Structure:

Our global network contained 8,035 dyads between 159 species nodes. We constructed

this network from five years of Wetland Bird Surbey data from the BTO, summarized in

Table 1A. thew structure of these networks were consistent over time, measured in their

species composition, and the relative edge weights between species pairs, given in

Table 1B. After filtering to only include species pairs which were also present in our viral

phylogeny, our data included 763 rows of 172 unique combinations of 19 species. Each

row, represented a species pair with an associated edge centrality (calculated from the

full networks, before filtering and scaling); pairwise weight (mean = 166.81; SD =

285.87) and SRI (mean = 0.005; SD = 0.005); and, three measures from our viral

phylogeny; maximum genetic distance between viral sequences (mean = 0.05; SD =

0.02), and mean Geometric (distance in m; 279121.8; 103676.6)- and temporal-distance

in days; 236.72; 115.93), all of which were repeated across networks.

Table 1A. Descriptive statistics for within-year social networks showing the number of species involved in the network (network nodes); the number of edges between species pairs, representing co-occurrence within a recording event, and, the number of recording events. A recording event represents a single survey visit in time and space. **1B.** Network similarity over years: **Upper right matrix** showing Jaccard similarity, the number of shared dyads between years irrespective of edge weight; and, **Lower left matrix**, Spearman rank correlation coefficients between dyadic edge weight between shared dyads, between years. In both cases 1 = perfect correlation and 0 = no relationship.

A. Network structure				B. Network similarity between years					
	Species	Edges	Events		2018	2019	2020	2021	2022
2018	115	4132	354	2018	-	0.67	0.65	0.56	0.56
2019	131	5321	729	2019	0.89	-	0.71	0.64	0.67
2020	127	4938	717	2020	0.86	0.91	-	0.66	0.63
2021	134	6378	782	2021	0.83	0.87	0.86	-	0.73
2022	137	6154	748	2022	0.79	0.85	0.85	0.91	-

Model outputs: We ran two models to test the relationship between wild bird social network structure and HPAI viral phylogenetic distance; the first used weight as a fixed effect and tested for a link between absolute co-occurrence (the number of shared events between a species dyad); and the second used the Simple Ratio Index of a species dyad to measure the extent that two species were recorded together over their opportunity for co-occurrence. We ran two models because pairwise weight and SRI are inherently correlated (Pearson's r = 0.91).

Pairwise weight: We tested the hypothesis that high co-occurrence should result in a greater chance of transmission between a species pair, and therefore closer genetic distance between viral sequences. We found a significant negative effect of pairwise weight on maximum genetic distance (95CI = -0.149 - -0.049; Estimate (or posterior mean) = -0.10), consistent with species that co-occur in the landscape had more closely related viral sequences than those that co-occurred less frequently. Scaled mean

geometric- (95CI = 0.02 - 0.136; Estimate = 0.07) and mean temporal distance (95CI =

0.35 - 0.43; Estimate = 0.39) both had a positive effect on maximum genetic distance,

confirming that sequences sampled closer in time and/or space were more similar to

one another.

SRI: SRI is a similar measure to pairwise weight, but, as well as shared recording

events, SRI also accounts for the opportunity for co-occurrence. A higher SRI is

therefore a measure of clustering probability in the social network. We tested the

hypothesis that high SRI (highly correlated dyads) should therefore predict close genetic

distance, as a proxy for interspecific HPAI virus transmission. Similarly to pairwise

weight, we found a negative association between scaled SRI and viral genetic distance

(95CI = -0.19 - -0.09; Estimate = -0.14), suggesting that frequent host co-occurrence is

associated with closer (maximum) genetic distance between viral sequences. scaled

mean geometric- (95CI = 0.01 - 0.012; Estimate = 0.06) and mean temporal distance

(95CI = -0.19 - -0.09; Estimate = -0.14) both were positively associated with the

maximum genetic distance, again, confirming the assumption that sequences sampled

closer in time and/or space were more similar to one an-other. Year did not explain

much variance in the model, supporting our assumption that networks constructed

between years represent broadly similar structures.

Permutations: To test if the identified associations were the result of community

structure, we also rewired network and repeated our models using an expected

distribution. In both cases, our observed estimate fell outside of the permuted (non-

Bayesian) confidence intervals of the permuted estimates: pairwise weight (95CI = -0.03

- 0.03) and SRI (95CI = -0.015 - 0.019), suggesting that our observed results are

unlikely to be the outcome of random chance. The significant positive effects of

geometric and temporal distance remained significant predictors of viral genome

similarity (see Figure 1:B).

Discussion: We combined a multi-species social network of waterbird co-occurrence from a location in England, United Kingdom, with recurrent HPAI outbreaks in wild birds and poultry, with an extensive database of HPAI viral genome samples. We tested the hypothesis that social proximity predicts the spread of disease through communities of wild animals, to support future surveillance of zoontic and epizootic diseases, prior to their emergence in humans or livestock. We found that both measures of social proximity, edge weight -a measure of raw co-occurrence in the landscape- and Simple Ratio Index (SRI) -a measure of 'connectedness' between two species, accounting for opportunity for co-occurrence- both predicted similarity in HPAI genome sequences. To do this, we accessed two large and open data repositories underscoring the value of such data to research into communities of wild animals. Although we used WeBS data from the British Trust for Ornithology, recent studies have also used similar open-data to infer multi-species networks of wild animals (Albery et al. 2020; Van Doren et al. 2025). Or, similarly, Vickers et al. (2024) used the eBird global repository of bird survey data (Sullivan et al. 2009) to link population dynamics in wild birds with HPAI incursion into poultry. In a social network context, previous studies have demonstrated transmission in simple, single species transmission systems (Hamede et al. 2009; Wilson-Aggarwal et al. 2019; Proboste et al. 2024), or, when applied to traits, in multi-species systems (Luis et al. 2015). Our results suggest, for the first time, that transmission of a disease of pandemic potential is also measurable through a multi-species network of wild animals, using social links as a proxy for transmission. This result is also predicted in the context of host- or environment traits, which drive pathogen transmission because they influence the shape of the social network, facilitating transmission by driving potential hosts into closer proximity (Hamede et al. 2009; Prosser et al. 2023; Jeglinski et al. 2024), facilitating social linkage. Our study demonstrates an empirical baseline for further theoretical predictive modelling of multi-species host-pathogen networks, by using the social links as a proxy for transmission to fill gaps in phylodynamic modelling.

Although our study represents a complex, multi-species transmission system, we did not make assumptions on the role of specific host traits in shaping contagion, within the community or at broader scales. Yet, although we have emperically demonstrated the

pathways of transmission between wild animals, it is host traits that drive transmission
through there social links, through traits that influence immuno-competence, or
behaviors triggered by the presence of disease in the community (S. Hill et al. 2016; N.
Hill et al. 2022; Pearce-Higgins et al. 2023; Jeglinski et al. 2024) or indirectly, by
shaping the social network through which disease is transferred, irrespective of the
presence of disease (for example, Firth, Sheldon, and Brent 2017; Firth et al. 2017;
Albery et al. 2022; Dunning et al. 2023; Schroeder et al. 2024). Our study focused on
spread at the landscape scale, for which we used multiple sites within a 50km buffer of
a farm with recurrent HPAI outbreaks in England. However, it is also likely that host
traits drive disease transmission at different scales, for example long-distance migration
has been associated with intercontinental HPAI transmission (Tian et al. 2015; McDuie
et al. 2024); Whereas, local outbreaks in poultry have been associated with short-
distance dispersal in sedentary game birds(Bourke et al. 2024; Gamża et al. 2024).

Our study focused on the social-links within a community of waterbirds, a natural
reservoir of HPAIs with inferred intermediate transmission (Humphreys et al. 2020;
Vickers et al. 2024), and for which we had community and viral genome data. We
accessed data on community structure from the BTO WeBS which only samples
waterbirds using repeated visits and a standardized methodology. As such, the edges in
our networks represented co-occurrence between a species pair within a recording
event, which we have demonstrated in a social network context (Dunning, Firth, and
Ward 2024), predicted similarity in HPAI genomes. However we note that a community
of wild animals may include multiple mechanisms of transmission, and our study is
appropriate only when applied to passive transmission systems. For example, our HPAI
viral genome database also included samples taken from predatory birds, raptors, that
had close genetic distances to colonial seabirds (Gamża et al. 2024). However, those
links are trophic, rather than social, and likely represent ingestion of infected prey,
rather than passive transmission. We therefore suggest that future studies should define
network edges by the mechanism of transmission, for example social links, mobility, or
predator-prey interactions, to study patterns of transmission.

We were able to use 763 pairwise genome samples, across years, of 172 unique dyads

of 19 host species for this study, but we were limited by the availability of genome data

for potential host species - our global social network, by comparison, comprised of

8,035 edges between 159 species nodes. Although the sub-graph (blue, within the

graph given in Figure 1) is sufficient as a proof of concept here, we suggest passive,

rather than reactive, sampling of wild animals where transmission is possible (also

suggested by Atkinson et al. 2025) would be beneficial to future study. Combined, our

results suggest that waterfowl social network structure, at the landscape scale, is stable

over time, and supports our hypothesis that species co-occurrence in the landscape is

linked with closer viral genetic similarity, implying measurable transmission through a

social network of wild birds.

Figure 1. **Panel A.** Of the 159 species in the co-occurrence network, 19 were also associated with a genome for highly pathogenic avian influenza clade 2.3.4.4b, of which we had access to 759 samples. The colour of the nodes and edges denotes that a species pair had viral genome data available, blue, or not, grey. The node size denotes normalised betweenness value, where 9.43, sits on the greatest number of shortest paths between all of dyads in the network, in this case Mute Swan *Cygnus olor*, and 0, on no of the shortest paths (here including Northern Lapwing *Vanellus Vanellus*, Little egret *Egretta garzetta*, and Northern pintail *Anas acuta*). **Panel B.** The expected distribution of permuted estimates in blue, with 95% confidence intervals - blue dotted lines, plotted against the observed estimate - red vertical line, for two measures of network structure – edge weight and Simple Ratio Index. In both cases, the observed estimate falls outside the permuted distribution, suggesting that closer social proximity predicts greater similarity in HPAI viral genome samples. This indicates that our results differ from what is expected when social structure is removed from the network.

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