

Biogeography and Environmental Conditions Shape Phage and Bacteria Interaction Networks Across the Healthy Human Microbiome

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Abstract

Viruses and bacteria are critical components of the human microbiome and play important roles in health and disease. Most previous work has relied on studying bacteria and phages in isolation, reducing them to two separate communities. Such approaches are not able to capture how these communities interact to maintain stability and share information (i.e. horizontal gene transfer). We developed and implemented a network-based analytical approach to provide an initial understanding of phage-bacteria network diversity throughout the human body. We accomplished this by building a machine learning algorithm to predict which phages infected which bacteria in a given microbiome. This algorithm was applied to paired viral and bacterial metagenomic sequence sets from three previously published human cohorts. We organized the predicted interactions into networks that allowed us to evaluate the diversity of phage-bacteria connectedness across the human body. We found that gut and skin network structures were person-specific, and were not conserved among cohabitating family members. High-fat diets and obesity were associated with less connected networks. There were significant differences in network structure between skin sites, with those exposed to the external environment being less connected and more prone to instability. Together this study characterized the diversity of virome-microbiome networks across the human body and illustrated how environmental factors may influence phage-bacteria interactive dynamics. This work provides a baseline for future studies to investigate the role of ecological networks in conditions such as disease states.

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Introduction

Viruses and bacteria are critical components to the human microbiome and play important roles in health and disease. Bacterial communities have been associated with diseases including a wide range of skin conditions (Hannigan and Grice 2013), acute and chronic wound healing conditions (Hannigan et al. 2014; Loesche et al. 2016), and gastrointestinal diseases including inflammatory bowel disease (He et al. 2016; Norman et al. 2015), *Clostridium difficile* infections (Seekatz et al. 2016), and colorectal cancer (Zackular et al. 2014; Baxter et al. 2014). Altered viromes (virus communities consisting primarily of bacteriophages in humans) have also been associated with various diseases and environmental perturbations including inflammatory bowel disease (Norman et al. 2015; Manrique et al. 2016), periodontal disease (Ly et al. 2014), spread of antibiotic resistance (Modi et al. 2013a), and others (Monaco et al. 2016; Hannigan et al. 2015; Minot et al. 2011; Santiago-Rodriguez et al. 2015; Abeles et al. 2015, 2014). These virus communities act in concert with bacteria as one single overall community (Haerter et al. 2014). Individual phages within these communities are capable of lysing their bacterial hosts, modulating their functionality through processes such as horizontal gene transfer (i.e. transduction) (Moon et al. 2015, Modi et al. (2013b), Ogg et al. (1981), Frost et al. (2005)), and altering bacterial host gene expression (Lindell et al. 2005, Tyler et al. (2013), Hargreaves et al. (2014)).

Most previous work has relied on studying bacterial and phage communities in isolation, reducing them to two separate communities (Norman et al. 2015; Manrique et al. 2016; Ly et al. 2014; Monaco et al. 2016; Hannigan et al. 2015; Minot et al. 2011; Santiago-Rodriguez et al. 2015; Abeles et al. 2015, 2014). In reality, bacteria and phage communities are dynamic and complex. They frequently share genetic information and work together to maintain stable ecosystems. Removal of members can disrupt or even collapse those ecosystems (Haerter et al. 2014; Harcombe and Bull 2005; Middelboe et al. 2001; Poisot et al. 2011, 2012; Thompson et al. 2012; Moebus and Nattkemper 1981; Flores et al. 2013, 2011; Poisot and Stouffer 2016; Jover et al. 2015). The most common approach to studying communities in isolation has been unable to capture how these communities interact and influence one another, but relationship-based network approaches allow us to capture this information. We aimed to bridge this knowledge gap by leveraging machine learning and graph theory techniques to characterize human bacterial and phage communities by their relationships. We focused on characterizing human skin and gut virome-microbiome network diversity to provide a foundation for further studies of disease network dynamics and to gain broader insights into human microbiome network diversity across different body sites.

First we investigated human microbiome-virome networks by utilizing three published microbiome datasets with paired

virus and bacterial metagenomic sequence sets (Hannigan et al. 2015; Minot et al. 2011; Reyes et al. 2010; Turnbaugh et al. 2009a). Our approach built off of previous large-scale phage-bacteria microbiome network analyses by inferring interactions using metagenomic datasets, instead of using culture-based techniques (Flores et al. 2013). This metagenomic interaction inference model was powered beyond previous models by its inclusion of protein interaction data as well as both negative and positive interactions (Edwards et al. 2015, Roux et al. (2016)).

Through this approach, we were able to go beyond contemporary isolated methods to provide a basic understanding of the community network dynamics associated with healthy human phages and bacteria. By building and utilizing a microbiome-virome network, we found that different people, body sites, and anatomical locations not only support distinct microbiome membership and diversity (Hannigan et al. 2015; Minot et al. 2011; Reyes et al. 2010; Turnbaugh et al. 2009a; Grice et al. 2009a; Findley et al. 2013; Costello et al. 2009, Consortium (2012)), but also support communities with distinct communication structures and propensities toward community instability. Through an improved understanding of the healthy state of network structures across the human body, we will empower future studies to begin investigating how these community structures change in disease and their overall impact on human health.

Results

Cohort Curation and Sample Processing

We studied the differences in virome-microbiome interaction networks across healthy human bodies by leveraging previously published sequence sets containing purified virome samples paired with bacterial metagenomes from whole metagenomic shotgun sequences. Our study contained three datasets, including a study of the impact of diet on the healthy human gut virome (Minot et al. 2011), the impact of anatomical location on the healthy human skin virome (Hannigan et al. 2015), and the viromes of monozygotic twins and their mothers (Reyes et al. 2010; Turnbaugh et al. 2009a). The viromes associated with these datasets were selected because they were subjected to virus-like particle (VLP) purification to eliminate other organismal DNA and allow for direct assessment of both the extracellular and actively replicating intracellular virome.

We utilized data that was published over the span of five years, which used different methods and technologies, and therefore yielded different sequence abundances (**Supplemental Figure S1 A-B**) (Minot et al. 2011, Hannigan et al. (2015), Reyes et al. (2010); Turnbaugh et al. 2009a). The bacterial and viral sequences from those publications were quality filtered and assembled into contigs. We generated clusters of related bacterial and phage contigs by k-mer

frequency and co-abundance using the CONCOCT algorithm (**Supplemental Figure S2 - S3**). We interpreted these clusters as operational units of related bacteria and phage genomes, which we defined as operational genomic units (OGUs). These OGUs are conceptually similar to the operational taxonomic unit (OTU) and operational protein family (OPF) definitions used for grouping highly similar 16S rRNA gene and open reading frame sequences, respectively (Schloss and Handelsman 2008).

Establishing a Model of Phage-Bacteria Interactions

We predicted which phage OGUs infected which bacterial OGUs using a random forest model trained on experimentally validated infectious relationships from six previous publications (Jensen et al. 1998; Malki et al. 2015; Schwarzer et al. 2012; Kim et al. 2012; Matsuzaki et al. 1992; Edwards et al. 2015). This training set contained 43 diverse bacterial species and 30 diverse phage strains, with both broad and specific infectious ranges (**Supplemental Figure S4 A - B**). Phages with linear and circular genomes, as well as ssDNA and dsDNA genomes, were included in the analysis. Because we used DNA sequencing studies, RNA phages were not considered (**Supplemental Figure S4 C-D**). This training set included both positive relationships (a phage infects a bacterium) and negative relationships (a phage does not infect a bacterium). This allowed us to validate the false positive and false negative rates associated with our candidate models, thereby building upon previous work that only considered positive relationships (Edwards et al. 2015).

Four phage and bacterial genomic features were used to predict infectious relationships between bacteria and phages: 1) genome nucleotide similarities, 2) gene amino acid sequence similarities, 3) Clustered Regularly Interspaced Short Palindromic Repeat (CRISPR) targeting of phages by bacterial CRISPR spacer sequences, and 4) similarity of protein families associated with experimentally identified protein-protein interactions (Orchard et al. 2014). The resulting random forest model performed with an AUC of 0.846, a sensitivity of 0.829, and a specificity of 0.767 (**Figure 1 A**). The most important predictor in the model was nucleotide similarity between genes, followed by nucleotide similarity of whole genomes (**Figure 1 B**). Protein family interactions were moderately important to the model, while CRISPRs were not informative (**Figure 1 B**). Approximately one third of the training set relationships yielded no score and were therefore unable to be assigned an interaction prediction (**Figure 1 C**).

Once our random forest model was built, we used it to classify the relationships between bacteria and phage operational genomic units in the experimental datasets. The relationships predicted within the three published datasets were used to construct one master network, which was built to contain the three studies as sub-networks, which themselves

each contained sub-networks for each sample (**Figure 1 D**). Metadata including study, sample ID, disease, and OGU abundance within the community were stored in the master network for downstream analysis (**Supplemental Figure S5**). The master network was highly connected and contained 72,287 infectious relationships among 578 nodes, 298 phages and 280 bacteria. Although the network was highly connected, not all relationships were present in all samples. As relationships were weighted by the relative abundances of their associated bacteria and phages, lowly abundant relationships could be present but not highly abundant. Like the master network, the skin network exhibited a diameter of 4 (measure of graph size; the greatest number of traversed vertices required between two vertices) and included 99.7% and 99.8% of the master network nodes and edges, respectively (**Figure 1 E - F**). The phages and bacteria in the gut diet and twin sample sets were more sparsely related, each contained fewer than 150 vertices, fewer than 20,000 relationships, and diameters of 3, which indicated more sparsely related phages and bacteria (**Figure 1 E - F**).

Role of Diet & Obesity in Gut Microbiome Connectivity

Diet is a major environmental factor that influences resource availability and gut microbiome composition and diversity, including bacteria and phages (Minot et al. 2011; Turnbaugh et al. 2009b; David et al. 2014). Previous work in isolated culture-based systems has suggested that changes in nutrient availability are associated with altered phage-bacteria network structures (Poisot et al. 2011), although this has yet to be tested in humans. We hypothesized that a change in diet would also be associated with a change in virome-microbiome network structure in the human gut.

We evaluated the diet-associated differences in gut virome-microbiome network structure by quantifying how central each sample's network was on average. We accomplished this by utilizing two common centrality metrics: degree centrality and closeness centrality. Degree centrality, the simplest centrality metric, was defined as the number of connections each phage made to bacteria, or each bacterium made to phages. We supplemented measurements of degree centrality with measurements of closeness centrality. Closeness centrality is a metric of how close each phage or bacterium is to all of the other phages and bacteria in the network. A higher closeness centrality suggests that the effects of genetic information or altered abundance would be more impactful to all other microbes in the system. A network with higher average closeness centrality also indicates an overall greater degree of connections, which suggests a greater resilience against instability. Because these values are assigned to each phage and bacterium within each network, we calculated the average connectedness and corrected for the maximum potential degree of connectedness to obtain a single value for the connectedness of each graph.

We found that the gut microbiome network structures associated with high-fat diets were less connected than those of

low-fat diets (**Figure 2 A-B**). Tests for statistical differences were not performed due to the small sample size. High-fat diets exhibited reduced degree centrality (**Figure 2 A**), suggesting bacteria in high-fat environments were targeted by fewer phages and that phage tropism was more restricted. High-fat diets also exhibited decreased closeness centrality (**Figure 2 B**), indicating that bacteria and phages were more distant from other bacteria and phages in the community. This would make genetic transfer and altered abundance of a given phage or bacterium less capable of impacting other bacteria and phages within the network.

In addition to diet, we also observed an association between obesity and network structure (**Figure 2 C-D**). The obesity-associated network demonstrated a higher degree centrality (**Figure 2 C**) but less closeness centrality compared to the healthy controls (**Figure 2 D**). These results suggest that the obesity network was overall less connected, having microbes further from all other microbes within the community.

Individuality of Microbial Networks

Skin and gut community membership and diversity are highly personal, with people remaining more similar to themselves over time compared to other people (Grice et al. 2009b; Hannigan et al. 2015; Minot et al. 2013). We therefore hypothesized that this personal conservation extended to microbiome network structure. To answer this hypothesis, we calculated the degree of dissimilarity between each subject's network, based on phage and bacteria abundance as well as centrality. We quantified phage and bacteria centrality within each sample graph using the weighted eigenvector centrality metric. This metric defines central phages as those that are highly abundant and infect many distinct bacteria which themselves are abundant and infected by many other phages. Similarly, bacterial centrality was defined as those bacteria that were both abundant and connected to numerous phages that were themselves connected to many bacteria. We then calculated the similarity of community networks using the weighted eigenvector centrality of all nodes between all samples. Samples with similar network structures were interpreted as having similar capacities for maintaining stability and transmitting genetic material.

We used this network dissimilarity metric to test whether microbiome network structures were more similar within people than between people over time. We found that gut microbiome network structure clustered by person (ANOSIM p-value = 0.005, $R = 0.958$, **Figure 3 A**). Network dissimilarity within each person over the 8-10 day sampling period was less than the average dissimilarity between that person and others, although this difference was not statistically significant (p-value = 0.125, **Figure 3 B**). The lack of statistical confidence was likely due to the small sample size of this dataset. Although there was evidence for gut network conservation among individuals, we found no evidence for conservation

of gut network structures within families. The gut network structures were not more similar within families (twins and their mothers; intrafamily) compared to other families (inter-family) (p-value = 0.312, **Figure 3 C**).

Skin microbiome network structure was strongly conserved within individuals (p-value < 0.001, **Figure 3 D**) and more adequately confirmed by our larger skin dataset. This distribution was similar when separated by anatomical sites, with most sites also being statistically significantly more conserved within individuals (**Supplemental Figure S6**).

Association Between Environmental Stability and Network Structure Across the Human Skin Landscape

Extensive work has illustrated differences in the healthy human skin microbiome between anatomical sites, including bacteria, viruses, and fungi (Grice et al. 2009b; Findley et al. 2013; Hannigan et al. 2015). These communities vary by degree of skin moisture, oil, and environmental exposure. We hypothesized that like microbial composition and diversity, microbial network structure would be specific to anatomical sites. We tested this hypothesis by evaluating the changes in network structure between anatomical sites within our skin dataset.

We quantified the average centrality of each sample using the weighted eigenvector centrality metric. We found that intermittently moist skin sites (dynamic sites that fluctuate between being moist and dry) were significantly less connected than the more stable moist and sebaceous environments (p-value < 0.001, **Figure 4 A**). We also found that skin sites that were protected from the environment (occluded) were much more highly connected than those that were constantly exposed to the environment or only intermittently occluded (p-value < 0.001, **Figure 4 B**).

We supplemented this analysis by comparing the network signatures using the centrality dissimilarity approach described above. The dissimilarity between samples was a function of shared relationships, degree of centrality, and bacteria/phage abundance. When using this supplementary approach, we found that network structures significantly clustered by moisture, sebaceous, and intermittently moist status (**Figure 4 C,E**). We also found that occluded sites were significantly different from exposed and intermittently occluded sites, but there was no difference between exposed and intermittently occluded sites (**Figure 4 D,F**). These findings provide further support that skin microbiome network structure differs significantly between skin sites.

Discussion

Early, foundational microbiome work has provided a baseline understanding of the human microbiome by characterizing bacteria and viral diversity across the human body, as well as other environments (Grice et al. 2009a; Findley et al. 2013; Hannigan et al. 2015; Costello et al. 2009, Consortium (2012); Schloss and Handelsman 2005; Minot et al. 2011). We similarly aimed to provide an initial understanding of how phage-bacteria networks differ throughout the human body, so as to provide a baseline for future studies of how microbiome networks differ in disease states. We developed and implemented a network-based analytical approach that we used to evaluate the basic properties of the human microbiome through bacteria and phage relationships, instead of membership or diversity. Through the use of network theory, we leveraged extensive analytical opportunities that could be applied to understand complex ecological communities. We utilized metrics of connectivity to model the extent to which communities of bacteria and phages interact (e.g. horizontal gene transfer, modulated bacterial gene expression, alterations in abundance). By pursuing this goal, we aimed to provide an initial understanding of human microbiome networks that will power future studies to use similar approaches in other settings, such as disease states.

We found that, just as gut microbiome and virome composition and diversity are conserved in individuals (Hannigan et al. 2015; Grice et al. 2009a; Findley et al. 2013; Minot et al. 2013), gut and skin microbiome network structures were also conserved within individuals over time. Gut network structure was not conserved among family members. These findings suggested that microbiome network properties, such as stability and the potential for horizontal gene transfer, were personal and may be impacted by personal factors ranging from the body's immune system to environmental conditions such as climate and diet. The ability of environmental conditions to shape gut and skin microbiome network structure was supported by our finding that diet and skin location were associated with altered network structures.

We found evidence that diet was sufficient to alter gut microbiome network connectivity. Although our sample size was small, our findings suggested that high-fat diets were less connected than low-fat diets. This suggested that high-fat diets may lead to less stable communities with a decreased ability for individuals to influence one other. We supported this finding with the observation that obesity was associated with decreased network connectivity (closeness of bacterial and phage vertices). Together these findings suggest the food we eat may not only impact which microbes colonize our guts, but may also impact their interactions. Further work will be required to characterize these relationships with a larger cohort.

In addition to diet, we found that skin microbiome network structure varied by skin environment. Network structure

230 differed between environmentally exposed and occluded skin sites. The sites under greater environmental fluctuation
231 and exposure, the exposed and intermittently exposed sites, were less connected and therefore were predicted to
232 have a higher propensity for instability. Likewise, intermittently moist sites demonstrated less connectedness than the
233 more stable moist and sebaceous sites. Thus body sites under greater degrees of fluctuation harbored less connected,
234 potentially less stable microbiomes.

235 Our results represent a step toward understanding the microbiome through interspecies relationships. While these
236 findings are informative, there are certainly caveats that should be noted. First, while our infection classification model
237 is advantageous over existing models, we recognize that, like most classification models, there remains opportunity
238 for improvement. For example, such a model is only as good as its training set. Large scale experimental screens
239 for phage and bacteria infectious interactions will provide more robust model training, and therefore improved model
240 performance. Just as we have improved on previous modeling efforts, we expect that new and creative scoring metrics
241 will be integrated into this model to further improve model performance.

242 Second, while an informative proof of concept, this work was done retrospectively and relied on published research from
243 as long as seven years ago. These archived datasets were limited by the technology and costs of the time, meaning
244 the datasets were poorly powered for the statistical analysis we strive for today. While we were able to present initial
245 conclusions, follow-up studies will be required to validate our findings. Despite their limitations, these methods and
246 results will be important for informing design and interpretation of future studies and for highlighting the importance of
247 bacteria-virus interaction profiles as a characteristic of human-associated microbial communities.

248 We overall demonstrated that microbiome relationship structure, and therefore the potential for microbiome genetic
249 transfer and stability maintenance, differed significantly between body sites. Other environmental factors, such as
250 diet and individuality, also influenced relationship structures of the microbiome. This information builds on previous
251 work by suggesting that bacteria and phages not only preferentially colonize different body sites, but also interact
252 differently, allowing for different communication structures and capacities for maintaining stability. Our results provide
253 a foundation for future studies to begin evaluating how microbiome network dynamics change in disease states, and
254 how the information can be applied therapeutically.

Materials & Methods

Data Availability

All associated source code is available on GitHub at the following repository:

https://github.com/SchlossLab/Hannigan_ConjunctisViribus_GenRes_2017

Data Acquisition & Quality Control

Raw sequencing data and associated metadata was acquired from the NCBI sequence read archive (SRA). Supplementary metadata was acquired from the same SRA repositories and their associated manuscripts. The gut virome diet study (SRA: SRP002424), twin virome studies (SRA: SRP002523; SRP000319), and skin virome study (SRA: SRP049645) were downloaded as .sra files. Sequencing files were converted to fastq format using the fastq-dump tool of the NCBI SRA Toolkit (v2.2.0). Sequences were quality trimmed using the Fastx toolkit (v0.0.14) to exclude bases with quality scores below 33 and shorter than 75 bp (Hannon). Paired end reads were filtered to exclude and sequences missing their corresponding pair using the get_trimmed_pairs.py available in the source code.

Contig Assembly

Contigs were assembled using the Megahit assembly program (v1.0.6) (Li et al. 2016). A minimum contig length of 1 kb was used. Iterative k-mer stepping began at a minimum length of 21 and progressed by 20 until 101. All other default parameters were used.

Contig Abundance Calculations

Contigs were concatenated into two master files prior to alignment, one for bacterial contigs and one for phage contigs. Sample sequences were aligned to phage or bacterial contigs using the Bowtie2 global aligner (v2.2.1) (Langmead and Salzberg 2012). We defined a mismatch threshold of 1 bp and seed length of 25 bp. Sequence abundance was calculated from the Bowtie2 output using the calculate_abundance_from_sam.pl script available in the source code.

Operational Genomic Unit Binning

Contigs often represent large fragments of genomes. In order to reduce redundancy, and the resulting artificially inflated genomic richness within our dataset, it was important to bin contigs into operational units based on their similarity. This approach is conceptually similar to the clustering of related 16S rRNA sequences into operational taxonomic units (OTUs), although here we are clustering contigs into operational genomic units (OGUs) (Schloss and Handelsman 2005).

We clustered contigs using the CONCOCT algorithm (v0.4.0) (Alneberg et al. 2014). Because of our large dataset and limits in computational efficiency, we randomly subsampled the dataset to include 25% of all samples, and used these to inform contig abundance within the CONCOCT algorithm. CONCOCT was used with a maximum of 500 clusters, a k-mer length of four, a length threshold of 1 kb, 25 iterations, and exclusion of the total coverage variable.

OGU abundance (A_O) was obtained as the sum of the abundance of each contig (A_j) associated with that OGU. The abundance values were length corrected such that:

$$A_O = \frac{10^7 \sum_{j=1}^k A_j}{\sum_{j=1}^k L_j}$$

Where L is the length of each contig j within the OGU.

Open Reading Frame Prediction

Open reading frames (ORFs) were identified using the Prodigal program (V2.6.2) with the meta mode parameter and default settings (Hyatt et al. 2012).

Classification Model Creation and Validation

The classification model for predicting interactions was built using experimentally validated bacteria-phage infections or validated lack of infections from six studies (Jensen et al. 1998; Malki et al. 2015; Schwarzer et al. 2012; Kim et al. 2012; Matsuzaki et al. 1992; Edwards et al. 2015). Associated reference genomes were downloaded from the European Bioinformatics Institute (see details in source code). The model was created based on the four metrics listed below.

The four scores were used as parameters in a random forest model to classify bacteria and bacteriophage pairs as either having infectious interactions or not. The classification model was built using the Caret R package (v6.0.73) (Kuhn). The model was trained using five-fold cross validation with ten repeats. Pairs without scores were classified as not interacting. The model was optimized using the ROC value. The resulting model performance was plotted using the plotROC R package.

Identify Bacterial CRISPRs Targeting Phages

Clustered Regularly Interspaced Short Palindromic Repeats (CRISPRs) were identified from bacterial genomes using the PilerCR program (v1.06) (Edgar 2007). Resulting spacer sequences were filtered to exclude spacers shorter than 20 bp and longer than 65 bp. Spacer sequences were aligned to the phage genomes using the nucleotide BLAST algorithm with default parameters (v2.4.0) (Camacho et al. 2009). The mean percent identity for each matching pair was recorded for use in our classification model.

Detect Matching Prophages within Bacterial Genomes

Temperate bacteriophages infect and integrate into their bacterial host's genome. We detected integrated phage elements within bacterial genomes by aligning phage genomes to bacterial genomes using the nucleotide BLAST algorithm and a minimum e-value of $1e-10$. The resulting bitscore of each alignment was recorded for use in our classification model.

Identify Shared Genes Between Bacteria and Phages

As a result of gene transfer or phage genome integration during infection, phages may share genes with their bacterial hosts, providing us with evidence of phage-host pairing. We identified shared genes between bacterial and phage genomes by assessing amino acid similarity between the genes using the Diamond protein alignment algorithm (v0.7.11.60) (Buchfink et al. 2015). The mean alignment bitscores for each genome pair was recorded for use in our classification model.

Protein - Protein Interactions

The final method we used for predicting infectious interactions between bacteria and phages was by detecting pairs of genes whose proteins are known to interact. We assigned bacterial and phage genes to protein families by aligning

them to the Pfam database using the Diamond protein alignment algorithm. We then identified which pairs of proteins were predicted to interact using the Pfam interaction information within the Intact database (Orchard et al. 2014). The mean bitscores of the matches between each pair were recorded for use in our classification model.

Virome Network Construction

The bacteria and phage operational genomic units (OGUs) were scored using the same approach as outlined above. The infectious pairings between bacteria and phage OGUs were classified using the random forest model described above. The predicted infectious pairings and all associated metadata were saved as a graph database using Neo4j graph database software (v2.3.1) (). This network was used for downstream community analysis.

Centrality Analysis

We quantified the centrality of graph vertices using three different metrics, each of which provided different information graph structure. When calculating these values, let $G(V, E)$ be an undirected, unweighted graph with $|V| = n$ nodes and $|E| = m$ edges. Also, let \mathbf{A} be its corresponding adjacency matrix with entries $a_{ij} = 1$ if nodes V_i and V_j are connected via an edge, and $a_{ij} = 0$ otherwise.

Briefly, the **closeness centrality** of node V_i is calculated taking the inverse of the average length of the shortest paths (d) between nodes V_i and all the other nodes V_j . Mathematically, the closeness centrality of node V_i is given as:

$$C_C(V_i) = \left(\sum_{j=1}^n d(V_i, V_j) \right)^{-1}$$

The distance between nodes (d) was calculated as the shortest number of edges required to be traversed to move from one node to another.

Intuitively, the **degree centrality** of node V_i is defined as the number of edges that are adjacent to that node:

$$C_D(V_i) = \sum_{j=1}^n a_{ij}$$

where a_{ij} is the ij^{th} entry in the adjacency matrix \mathbf{A} .

The eigenvector centrality of node V_i is defined as the i^{th} value in the first eigenvector of the associated adjacency matrix \mathbf{A} . Conceptually, this function results in a centrality value that reflects the connections of the vertex, as well as the centrality of its neighboring vertices.

The **centralization** metric was used to assess the average centrality of each sample graph G . Centralization was calculated by taking the sum of each vertex V_i 's centrality from the graph maximum centrality C_w , such that:

$$C(G) = \frac{\sum_{i=1}^n C_w - c(v_i)}{T}$$

The values were corrected for uneven graph sizes by dividing the centralization score by the maximum theoretical centralization (T) for a graph with the same number of vertices.

Degree and closeness centrality were calculated using the associated functions within the igraph R package (v1.0.1) (Csardi and Nepusz).

Network Relationship Dissimilarity

We assessed similarity between graphs by evaluating the shared centrality of their vertices, as has been done previously. More specifically, we calculated the dissimilarity between graphs G_i and G_j using the Bray-Curtis dissimilarity metric and eigenvector centrality values such that:

$$B(G_i, G_j) = 1 - \frac{2C_{ij}}{C_i + C_j}$$

Where C_{ij} is the sum of the lesser centrality values for those vertices shared between graphs, and C_i and C_j are the total number of vertices found in each graph. This allows us to calculate the dissimilarity between graphs based on the shared centrality values between the two graphs.

Statistics and Comparisons

Differences in intrapersonal and interpersonal network structure diversity, based on multivariate data, were calculated using an analysis of similarity (ANOSIM). Statistical significance of univariate Eigenvector centrality differences were calculated using a paired Wilcoxon test.

Statistical significance of differences in univariate eigenvector centrality measurements of skin virome-microbiome networks were calculated using a pairwise Wilcoxon test, corrected for multiple hypothesis tests using the Holm correction method. Multivariate eigenvector centrality was measured as the mean differences between cluster centroids, with statistical significance measured using an ANOVA and post hoc Tukey test.

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Disclosure Declaration

The authors report no conflicts of interest.

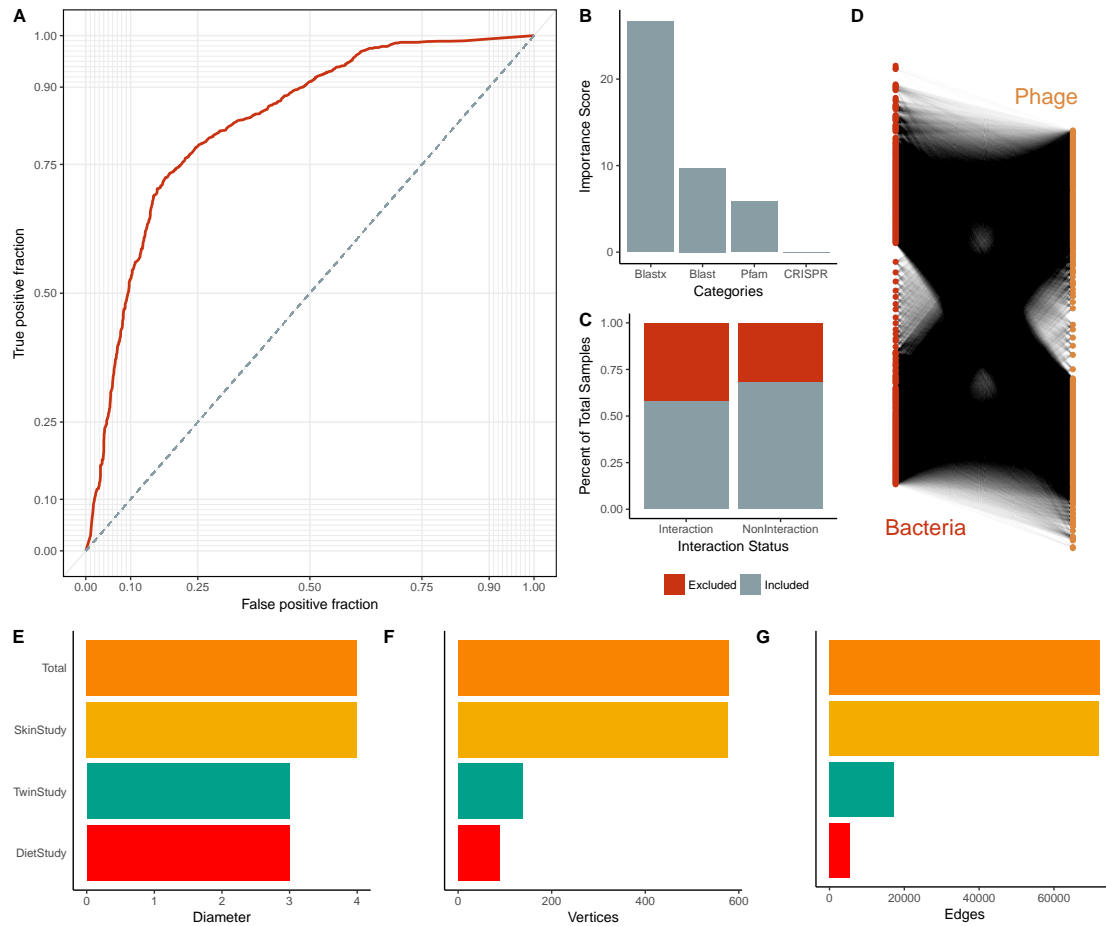


Figure 1: Summary of Multi-Study Network Model. (A) Average ROC curve used to create the microbiome-virome infection prediction model. (B) Importance scores associated with the metrics used in the random forest model to predict relationships between bacteria and phages. The importance score is defined as the mean decrease in accuracy of the model when a feature (e.g. Pfam) is excluded. (C) Proportions of samples included (gray) and excluded (red) in the model. Samples were excluded from the model because they did not yield any scores. Those interactions without scores were defined as not having interactions. (D) Bipartite visualization of the resulting phage-bacteria network. This network includes information from all three published studies. (E) Network diameter (measure of graph size; the greatest number of traversed vertices required between two vertices), (F) number of vertices, and (G) number of edges (relationships) for the total network (yellow) and the individual study sub-networks (diet study = red, skin study = green, twin study = orange).

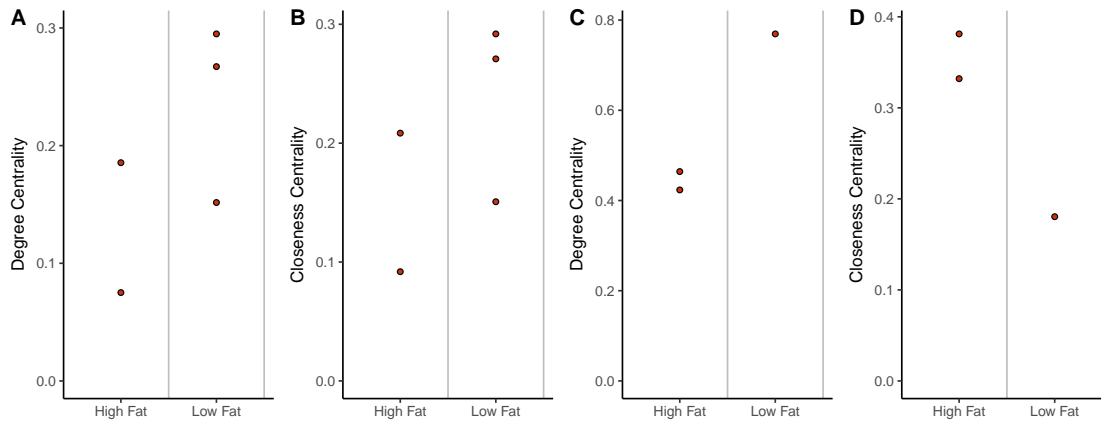


Figure 2: Impact of Diet and Obesity on Gut Network Structure. (A) Quantification of average degree centrality (number of edges per node) and (B) closeness centrality (average distance from each node to every other node) of gut microbiome networks of subjects limited to exclusively high-fat or low-fat diets. Lines represent the mean degree of centrality for each diet. (C) Quantification of average degree centrality and (D) closeness centrality between obese and healthy adult women.

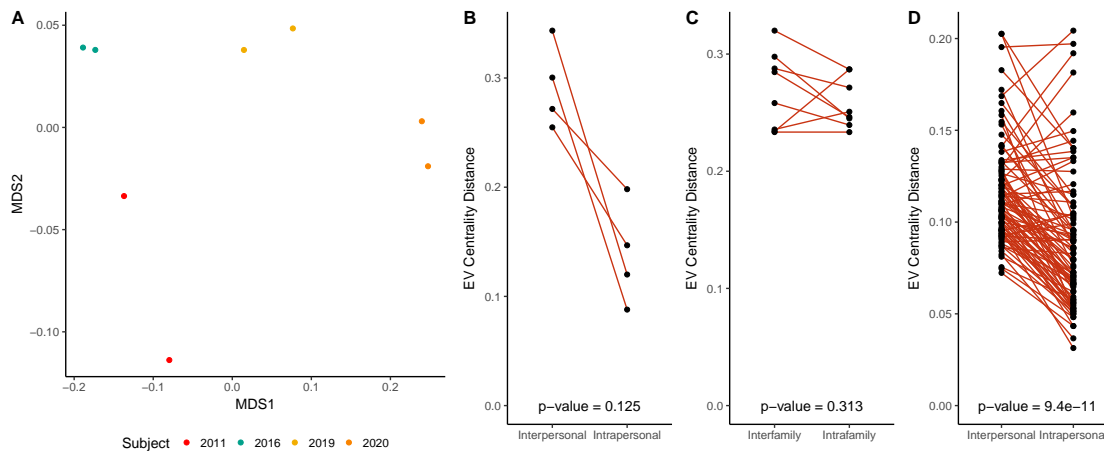


Figure 3: Intrapersonal vs Interpersonal Network Dissimilarity Across Different Human Systems. (A) NMDS ordination illustrating network dissimilarity between subjects over time. Each sample is colored by subject, with each sample pair collected 8-10 days apart. Dissimilarity was calculated using the Bray-Curtis metric based on abundance weighted eigenvector centrality signatures, with a greater distance representing greater dissimilarity in bacteria and phage centrality and abundance. (B) Quantification of gut network dissimilarity within the same subject over time (intrapersonal) and the mean dissimilarity between the subject of interest and all other subjects (interpersonal). The p-value is also provided. (C) Quantification of gut network dissimilarity within subjects from the same family (intrafamily) and the mean dissimilarity between subjects within a family and those of other families (interfamily). The p-value is also provided. (D) Quantification of skin network dissimilarity within the same subject and anatomical location over time (intrapersonal) and the mean dissimilarity between the subject of interest and all other subjects at the same time and the same anatomical location (interpersonal). P-value was calculated using a paired Wilcoxon test.

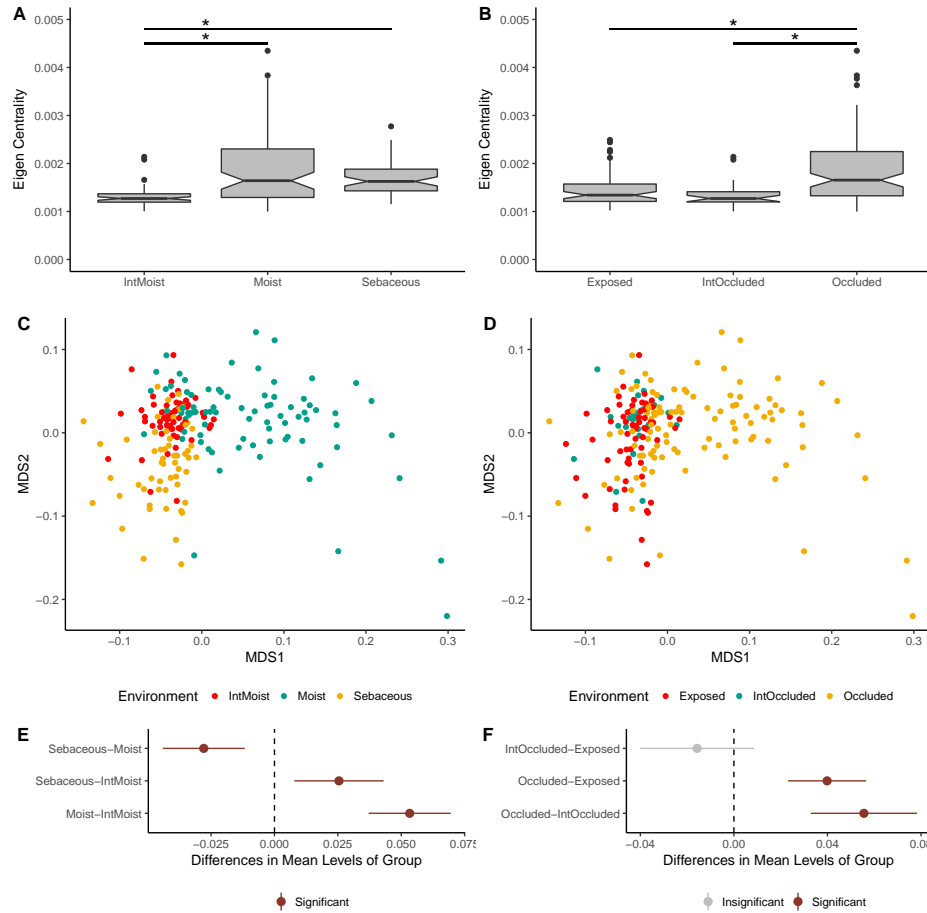


Figure 4: Impact of Skin Micro-Environment on Microbiome Network Structure. (A) Notched box-plot depicting differences in average eigenvector centrality between moist, intermittently moist, and sebaceous skin sites and (B) occluded, intermittently occluded, and exposed sites. Notched box-plots were created using ggplot2 and show the median (center line), the inter-quartile range (IQR; upper and lower boxes), the highest and lowest value within $1.5 \times \text{IQR}$ (whiskers), outliers (dots), and the notch which provides an approximate 95% confidence interval as defined by $1.58 \times \text{IQR} / \sqrt{n}$. (C) NMDS ordination depicting the differences in skin microbiome network structure between skin moisture levels and (D) occlusion. Samples are colored by their environment and their dissimilarity to other samples was calculated as described in figure 3. (E) The statistical differences of networks between moisture and (F) occlusion status were quantified with an anova and post hoc Tukey test. Cluster centroids are represented by dots and the extended lines represent the associated 95% confidence intervals. Significant comparisons ($p\text{-value} < 0.05$) are colored in red, and non-significant comparisons are gray.

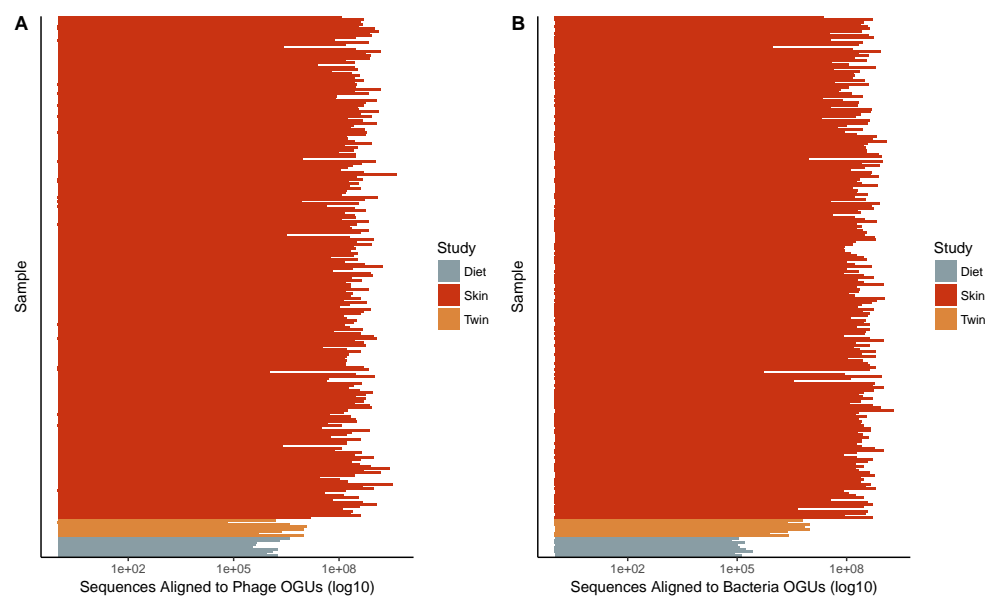


Figure S1: **Sequencing Depth Summary.** Number of sequences that aligned to (A) Phage and (B) Bacteria operational genomic units per sample and colored by study.

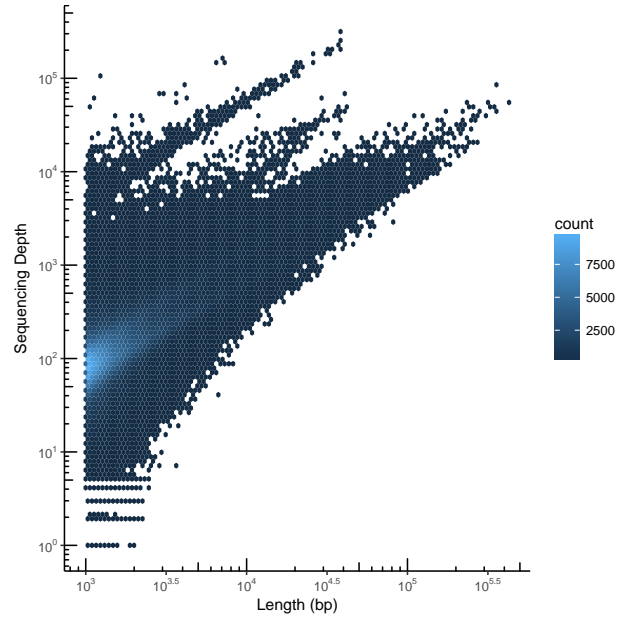


Figure S2: **Contig Summary Statistics.** Scatter plot heat map with each hexagon representing the abundance of contigs. Contigs are organized by length on the x-axis and the number of aligned sequences on the y-axis.

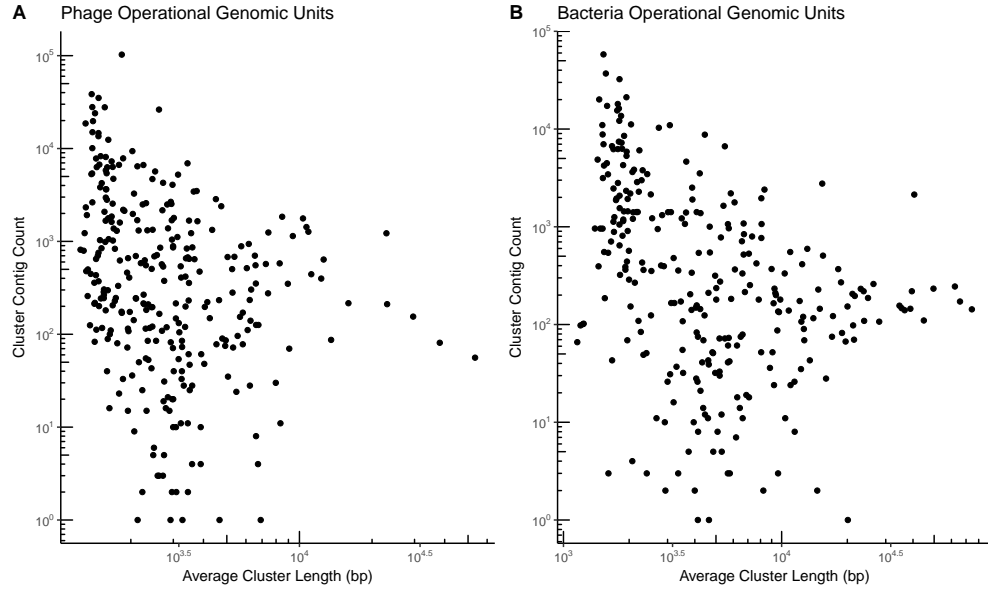


Figure S3: **Operational Genomic Unit Summary Statistics.** Scatter plot with operational genomic unit clusters organized by average contig length within the cluster on the x-axis and the number of contigs in the cluster on the y-axis. Operational genomic units of (A) bacteriophages and (B) bacteria are shown.

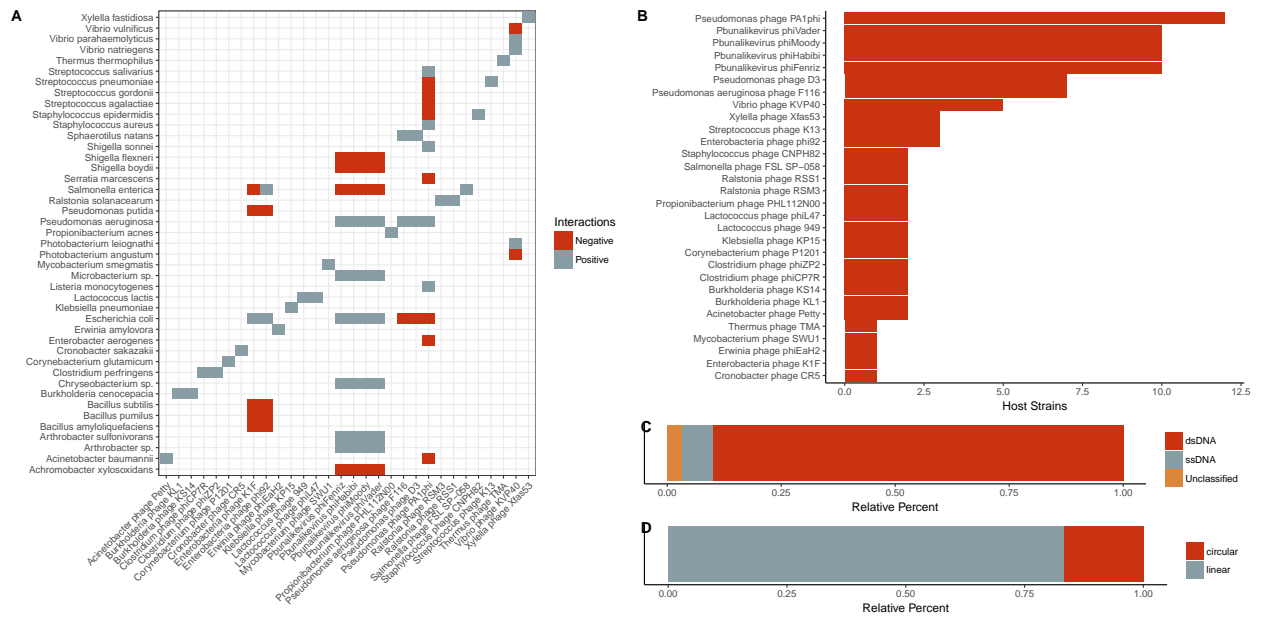


Figure S4: **Summary information of validation dataset used in the interaction predictive model.** A) *Categorical* heat-map highlighting the experimentally validated positive and negative interactions. Only bacteria species are shown, which represent multiple reference strains. Phages are labeled on the x-axis and bacteria are labeled on the y-axis. B) *Quantification* of bacterial host strains known to exist for each phage. C) *Genome strandedness* and D) *linearity* of the phage reference genomes used for the dataset.

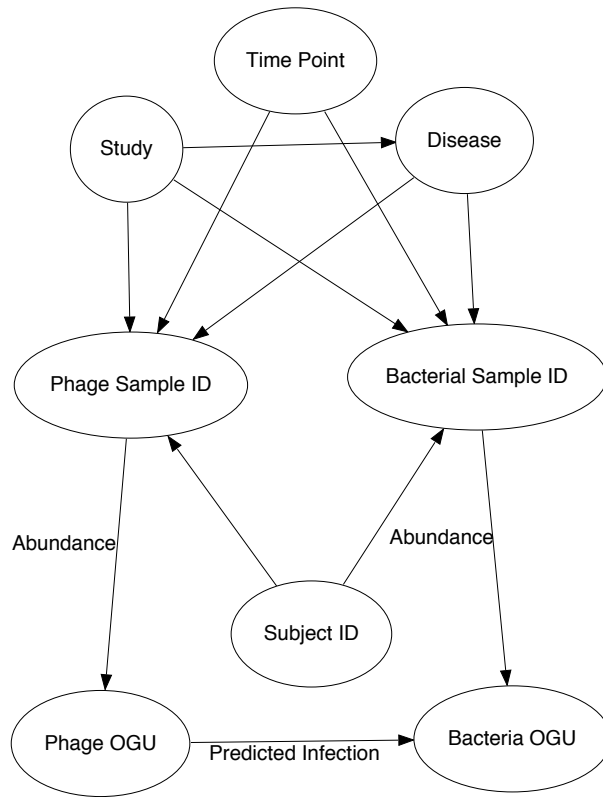


Figure S5: **Structure of the interactive network.** Metadata relationships to samples (Phage Sample ID and Bacteria Sample ID) included the associated time point, the study, the subject the sample was taken from, and the associated disease. Infectious interactions were recorded between phage and bacteria operational genomic units (OGUs). Sequence count abundance for each OGU within each sample was also recorded.

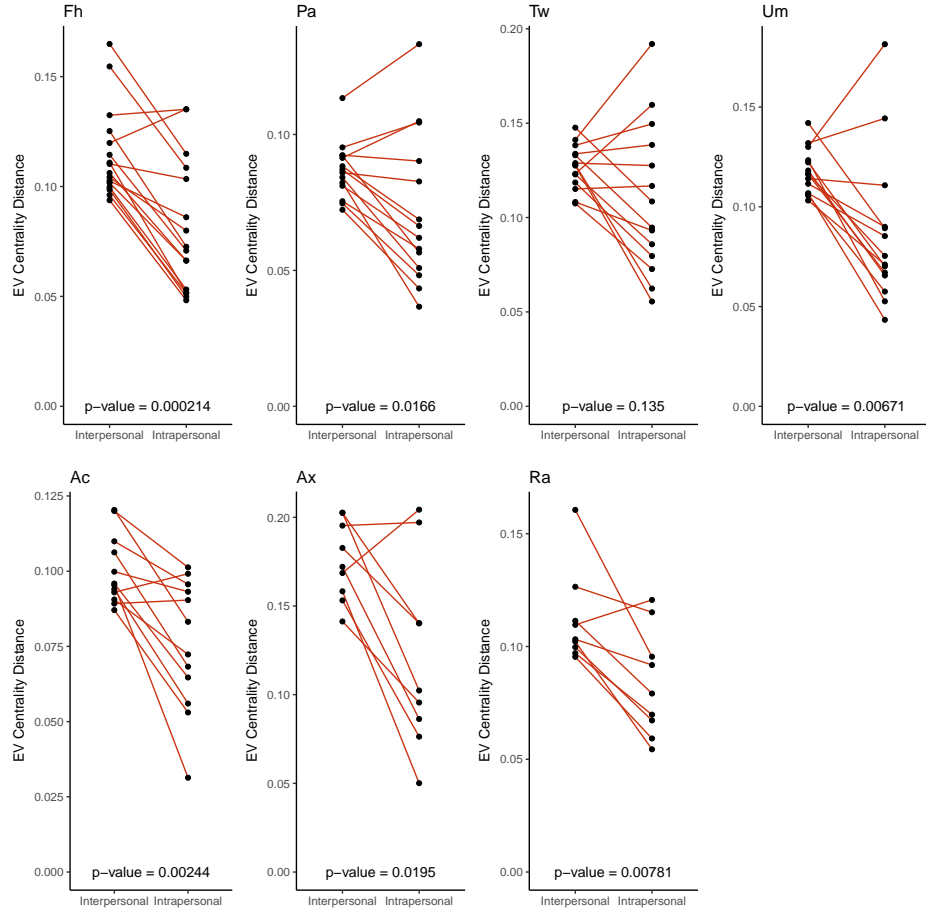


Figure S6: Intrapersonal vs Interpersonal Dissimilarity of the Skin. Quantification of skin network dissimilarity within the same subject and anatomical location over time (intrapersonal) and the mean dissimilarity between the subject of interest and all other subjects at the same time and the same anatomical location (interpersonal), separated by each anatomical site (forehead [Fh], palm [Pa], toe web [Tw], umbilicus [Um], antecubital fossa [Ac], axilla [Ax], and retroauricular crease [Ra]). P-value was calculated using a paired Wilcoxon test.

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