# Metagenomic evidence for a healthy human blood microbiome

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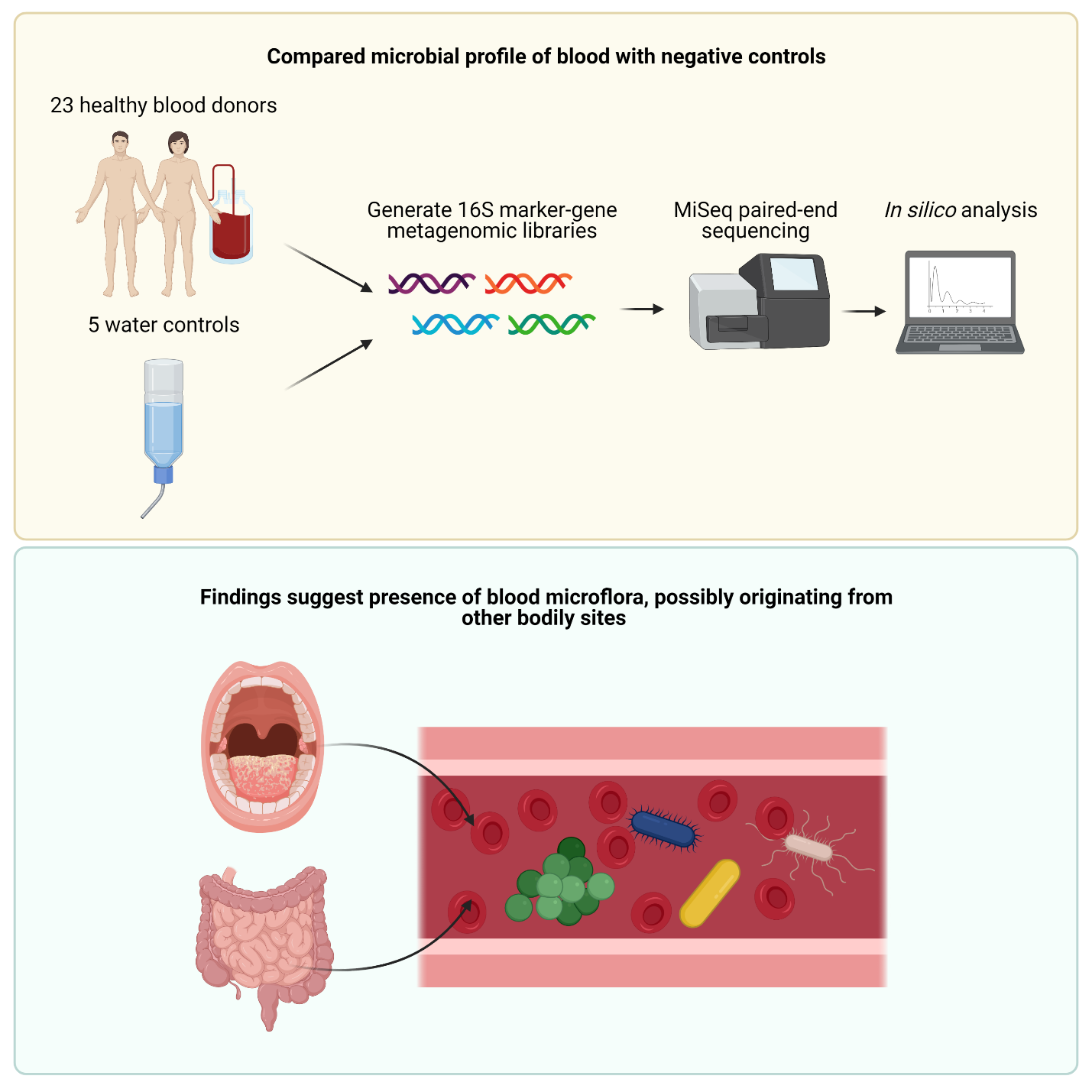
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# Highlights

* There is evidence for a healthy blood microbiome
* Putative members of this microbiome can be computationally identified from metagenomic sequencing data
* Putative members of this microbiome may have translocated from other bodily sites

# Graphical abstract



# Summary

Human blood has traditionally been considered be devoid of microorganisms, where their occasional entry is believed to cause bloodstream infections associated with high mortality and morbidity. This study sought to determine whether blood is indeed sterile. 16S ribosomal RNA metagenomic sequencing was performed on 23 blood samples from clinically healthy donors and five water controls, and their resultant microbial taxonomic profiles compared. The taxonomic profiles of blood samples were clearly distinct from that of controls, suggesting that most of the microbial sequences detected in blood are not the result of sequencing contamination. This supports the hypothesis of a blood microbiome. Further, *in silico* analysis of the sequences suggest that some of the putative members of this microbiome may have translocated from other bodily sites such as the gut or oral cavity.

# Introduction

In recent years, an increasing number of studies have reported bacterial DNA or even culturable bacteria in the blood of apparently ‘healthy’ individuals (*i.e.* with no clinical symptoms of disease) (reviewed by Castillo *et al.* (2019)). These studies sought to investigate two main questions: is there a blood microbiome? If there is, what does its microbial profile look like? To do so, most studies have employed culture-based or sequencing approaches. The former approach involves the use of microbiological cultures of blood samples; the latter involves either targeted 16S marker-gene, or non-targeted ‘shotgun’ metagenomic sequencing of microbial DNA extracted from blood. Both approaches have their advantages and limitations. Culture-based methods demonstrate the viability of detected microorganisms. However, they cannot detect ‘unculturable’ microorganisms and have a notoriously low sensitivity, especially when the bacterial load is low (Benjamin and Wagner, 2007). Additionally, the microorganisms detected are largely biased by the type of culture medium used. This approach therefore prevents a comprehensive characterisation of the breadth of blood microorganisms.

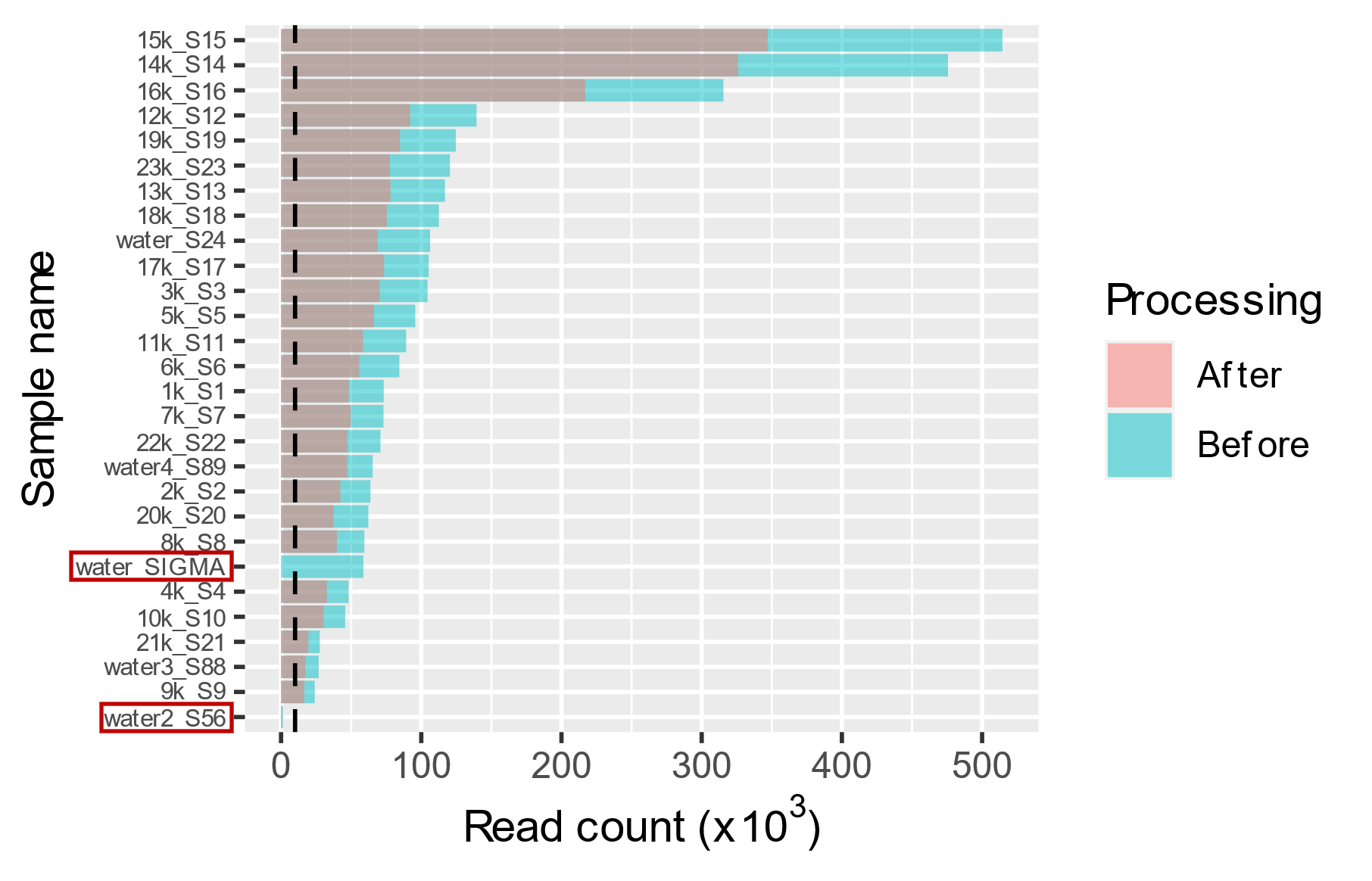
On the other hand, metagenomic sequencing can detect unculturable or low abundance microorganisms, and is therefore a more sensitive approach for profiling the blood microbiome. The main trade-off for this increased sensitivity is that sequencing is highly prone to environmental contamination. Contaminant DNA from laboratory reagents, referred to as the ‘kitome’, can be introduced during sample processing (Salter *et al.*, 2014; Weiss *et al.*, 2014; Glassing *et al.*, 2016). Alternatively, contaminant DNA may be introduced when using non-sterile equipment or poor aseptic technique during sample collection. These contaminating sequences are known to skew biological inferences of metagenomic sequencing data, particularly for sample types with low microbial biomass such as blood (Eisenhofer *et al.*, 2019). Delineating contaminant DNA sequences from those endogenous to blood is therefore crucial in lending weight to arguments for a blood microbiome. However, as Castillo *et al.* (2019) noted, experimental controls for addressing the contamination problem are often omitted in blood microbiome studies. Even when controls are included, they are often only used for quantifying the overall level of contamination introduced by the experimental protocols used (Païssé *et al.*, 2016; Gosiewski *et al.*, 2017). Such controls should ideally be used to identify and remove putative contaminant taxa before making any biological inference of the taxonomic profiles observed.

In this study, 16S marker-gene metagenomic sequencing (henceforth ‘16S sequencing’) was performed on microbial DNA extracted from the blood of 23 clinically healthy individuals to characterise the hypothetical human blood microbiome. To address the problem of contamination, five negative controls were also sequenced in the same sequencing run, and their taxonomic profiles compared at the genus level. These controls had sterile water in place of DNA extracted from blood and were used to account for contaminant sequences introduced during library preparation and sequencing. Indeed, since the microbial taxa observed in the negative controls are assumed to be contaminants, these taxa can be selectively omitted to produce a more accurate depiction of the microbial composition in blood. The results suggest that the number and relative abundance of microbial taxa detected differed between the two sample types. This implies that the microbial sequences found in healthy human blood are more likely to originate from endogenous bacteria rather than from contamination sources during library preparation, providing support for the existence of a human blood microbiome.

# Results

## 16S metagenomic sequencing

Sequencing of the hypervariable region spanning V3-V4 of the bacterial 16S ribosomal RNA (rRNA) gene was performed to characterise the microbial composition of 23 healthy human blood samples and five negative water controls. A total of 3,205,568 paired-end reads were generated for all 28 samples in a single sequencing run, and 2,120,549 reads were retained after all read processing steps. The distribution of reads per sample before and after these processing steps (**Figure 1**) suggests that most samples had a reasonable sequencing depth and overall read quality. Two negative controls with less than 10,000 reads are considered potentially problematic samples but were not excluded from further analysis to avoid introducing additional biases.



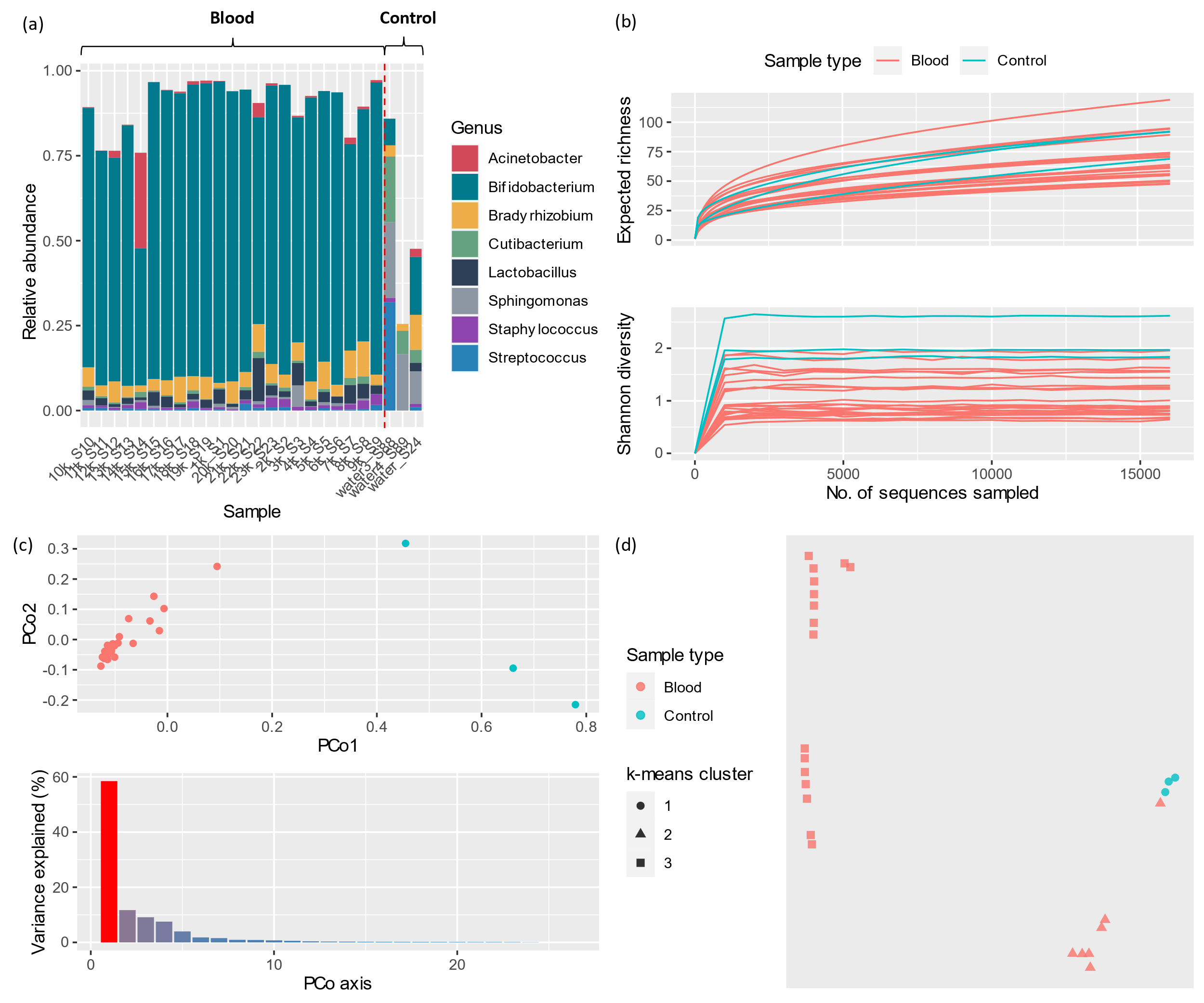
**Figure 1. Per-sample distribution of reads.** The read counts of samples before and after all read processing steps were extracted from the respective FASTQ files and visualised. The black dashed line indicates the read count threshold of 10,000 reads. Negative controls that were excluded are denoted by red boxes.

## Healthy human blood and negative controls have distinct microbial compositions

Taxonomic classification of the processed reads for each sample was performed using *Kraken 2* (Wood, Lu and Langmead, 2019). This strategy was used instead of conventional 16S metagenomic analysis pipelines such as *QIIME 2* (Bolyen *et al.*, 2019) since *Kraken 2* was shown to be faster and more accurate (Lu and Salzberg, 2020). Additionally, since there is less uncertainty in taxonomic assignments at the genus than at the species level (Simon *et al.*, 2019), the taxonomic assignments were only used to calculate the relative abundance of genera for downstream analyses. The relative abundance of the eight most abundant genera in blood samples and in controls were visually distinct (**Figure 2a**). For example, *Bifidobacterium* predominates in blood samples, but not in the negative controls. To determine if the diversity of microbial sequences differed between the sample types, the genus richness and Shannon index (Shannon, 1948) for each sample was compared. Rarefaction was performed to account for the different sequencing depths for each sample (**Figure 1**). Blood samples and controls had comparable genus richness, but blood samples had a visibly lower Shannon index (**Figure 2b**). The Shannon index is a measure of both the number of genera (*i.e.* richness) and how equal the relative abundance of genera are (*i.e.* evenness). A higher Shannon index indicates a higher richness and/or evenness. Since the genus richness for the two sample types were comparable, the lower Shannon index for blood samples indicate a lower evenness, which is likely driven by the excess of *Bifidobacterium* sequences.

To further determine whether the microbial composition of the two sample types could be distinguished, ordination using principal coordinates analysis (PCoA) was performed. The first principal coordinate axis separated the two sample types clearly (**Figure 2c**; upper panel) and accounted for a major proportion of variation in the relative abundance data (58.5%; lower panel). Additionally, *t*-distributed stochastic neighbour embedding (*t*-SNE) was used to identify groups of samples with similar microbial compositions in an unsupervised fashion. In this context, *t*-SNE projects the relative genera abundance for each sample on a two-dimensional space, where samples with more similar microbial compositions are brought closer together, and those with dissimilar compositions further apart. Echoing the results of the PCoA, blood samples could be spatially separated from the negative controls (**Figure 2d**). The results of the two analyses collectively suggest that the two sample types have distinct microbial compositions. Interestingly, the blood samples appear to form more than one cluster on the *t*-SNE projection (**Figure 2d**). *k*-means clustering, which can classify samples with similar microbial compositions into groups, confirmed that blood samples could be classified into two groups, in addition to a separate negative control group. The agreement of both *t*-SNE and *k*-means clustering indicates that this observation is not likely to be an artifact of the computational methods used. This finding suggests that the hypothetical healthy blood microbiome may be categorised into different subtypes, where each subtype harbours a signature microbial composition.

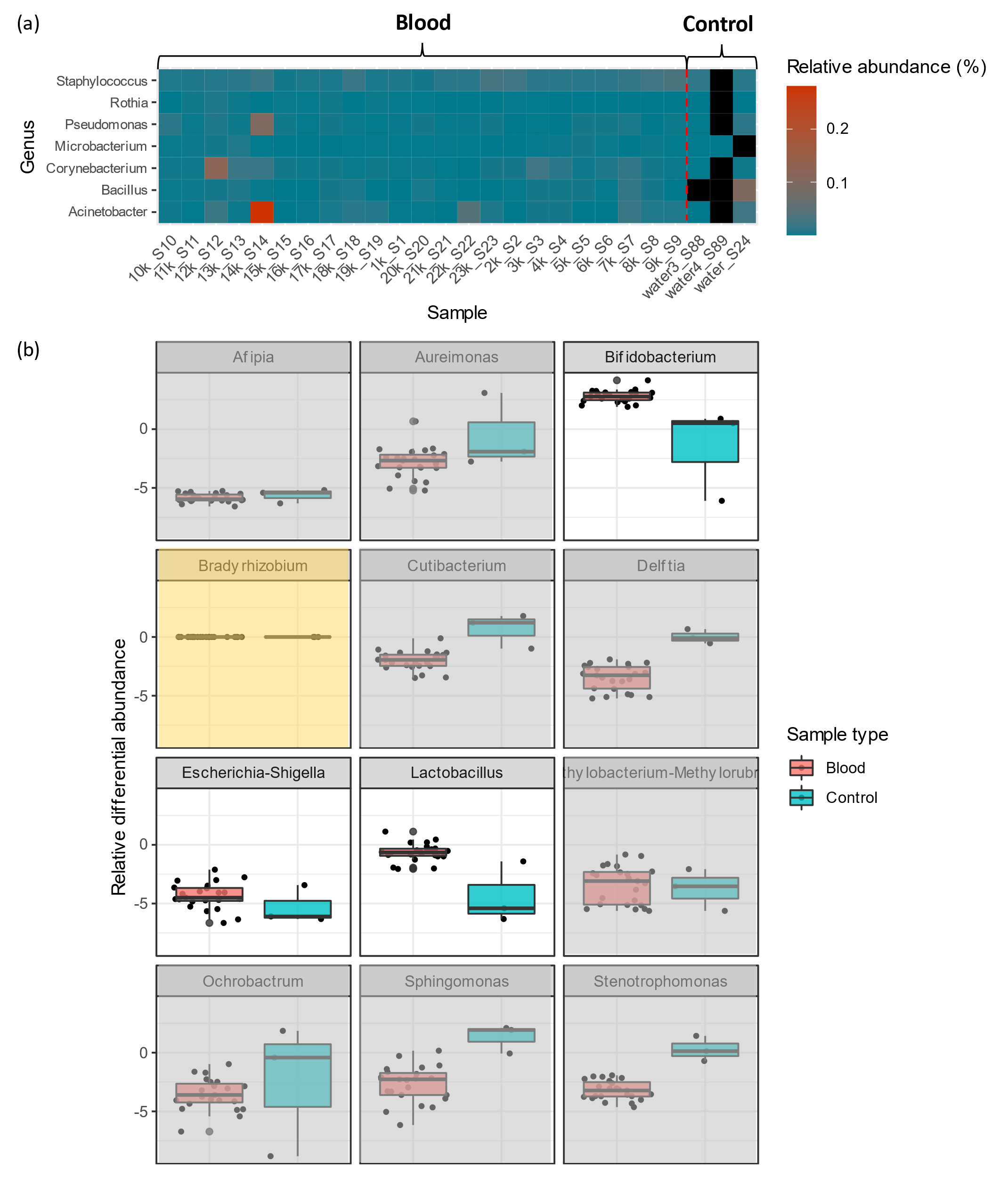
Taken together, the results indicate that the number and composition of microbial genera in blood samples can be distinguished from that in the negative controls. This implies that the microbial sequences in blood are not solely due to contamination from sequencing reagents, suggesting the presence of DNA from potentially viable bacteria in healthy human blood.



**Figure 2. Microbial composition and diversity of healthy blood and negative controls.** (a) Relative abundance of the eight most abundant genera (ranked by their median values across all samples) are visualised in a stacked bar-plot. (b) Rarefaction plots of genus richness and Shannon index. (c) Upper panel: PCoA plot of all samples on the first two PCo axes. Each point represents a single sample after ordination using PCoA. Lower panel: Percentage of variance explained by each PCo axis. (d) *t-*SNE plot projecting the relative genera abundance of samples on a two-dimensional space. Each point represents a single sample after ordination using *t*-SNE. The shape of each point represents the clusters identified using the *k*-means clustering algorithm.

## Candidate members of the human blood microbiome

Since all samples were processed and sequenced in the same batch, the taxonomic assignments for the negative controls could be used to identify potential microbiome-associated genera while excluding putative contaminants. Firstly, seven genera were found in all blood samples, but absent in at least one negative control (**Figure 3a**). Species within these genera present as preliminary targets for members of the blood microbiome. Notably, some genera are present in all samples, but may also be part of the human blood microbiome. One way to determine whether such genera are microbiome-associated or contaminants is to compare their relative abundance in blood and in controls (Salter *et al.*, 2014). This is because taxa that are present in a true microbial community are likely to be highly abundant in microbiome samples and less abundant in negative controls. Conversely, contaminant taxa are likely to be highly abundant in controls but not in samples. Therefore, the measured relative abundance of taxa is a good proxy for selecting candidate members of the human blood microbiome. However, if there is a microbial community in blood, blood samples should have a higher microbial load than negative controls. This differing microbial load is known to confound comparisons of relative abundance (Morton *et al.*, 2019). As such, relative differential abundance (RDA), where the relative abundance of a particular taxon is normalised by a reference taxon in the same sample (see Methods), was compared. RDA controls for the differing microbial loads in samples when comparing relative abundances. Using *Bradyrhizobium* as the reference genus, the RDA of genera that were found in all samples were computed. Of the twelve genera that were present in all samples, only *Bifidobacterium*, *Lactobacillus* and *Escherichia-Shigella* appeared to be more abundant in blood than in controls (**Figure 3b**). These genera are therefore candidate members of the human blood microbiome.



**Figure 3.** (a) Heatmap showing the relative abundance of genera that are found in all blood samples but not in all negative controls. Each tile represents the relative abundance of a single genus for a particular sample. Black tiles indicate a relative abundance of zero. (b) Boxplots of RDA for genera that were present in all samples. Each point represents a single sample. Panels that are not likely candidate members of the human blood microbiome are shaded grey, and the reference frame is shaded yellow.

# Discussion

## The potential healthy human blood microbiome

This study demonstrates that many of the microbial sequences detected in healthy human blood are not likely to originate from sequencing reagents and may be associated with an active microbial community. Moreover, *in silico* analysis of blood and negative controls allowed the careful identification of potential members of the hypothetical blood microbiome (**Figure 3**), which are prime targets for further experimental validation. Some of these genera have been identified in human blood samples previously. For example, *Acinetobacter*, *Staphylococcus,* *Pseudomonas* and *Bacillus* species were isolated from at least one healthy blood sample via microbiological culture, with *S*. *epidermis* found in 23% of samples (Damgaard *et al.*, 2015). This indicates that live microbial cells from said genera can indeed be found in healthy human blood. Additionally, in another metagenomic sequencing study involving 30 healthy French blood donors, *Acinetobacter*, *Escherichia/Shigella*, *Corynebacterium*, *Pseudomonas*, and *Staphylococcus* sequences were also found (Païssé *et al.*, 2016). Given that different experimental protocols were used, and that the samples were from a different cohort, these findings serve as independent validation of our results.

Separately, our results suggest that the gut and mouth may be potential sources of the bacteria found in blood. For example, *Bifidobacterium*, *Lactobacillus* and *Rothia* are often found in the human oral cavity (Marsh, 2000; Hojo *et al.*, 2007) and gastrointestinal tract (Reuter, 2001; Turroni *et al.*, 2014). The detection of these genera in blood suggests that they may have translocated from other bodily sites via breaches in the mucosal barrier. In fact, the translocation of bacteria across the intestinal wall has been previously described (Berg, 1999). In particular, *Bifidobacterium breve* has even been used as an orally administered vehicle for delivering anti-cancer therapeutic agents to tumour cells (Cronin *et al.*, 2010). Since bacteria can penetrate mucosal barriers and bloodstream is a nutrient rich environment, it seems plausible that bacterial cells from other bodily sites can colonise and establish a microbial community in blood. Moreover, micrographs of human blood suggest that bacteria can reside within red blood cells in as L-forms (Potgieter *et al.*, 2015). L-form refers to a bacterium that has lost some or all of its cell wall. This is a potential mechanism for bacteria translocated from other bodily sites to establish themselves in the bloodstream.

One interesting observation is the clustering of blood microbial abundance profiles into distinct groups (**Figure 2d**). If a blood microbiome exists, the presence of microbiome subtypes would be unsurprising. Indeed, demographic factors and health status are known to affect the microbiome of other bodily sites. For instance, age, blood biomarkers and even mineral supplement consumption were found to be associated with the composition and diversity of the human gut microbiome (Scepanovic *et al.*, 2019). Variation in the demography or behaviour of the clinically ‘healthy’ individuals recruited in the present study may therefore account for the clustering of the blood taxonomic profiles. However, the unavailability of such information precluded further analysis. Overall, while the results hint at the presence of blood microbiome subtypes, this needs to be evidenced by larger-scale experimental and *in silico* investigations.

## Practical implications of the potential blood microbiome

Bacteria in the human microbiome are known to interact extensively with their hosts. For example, gut bacteria are known to convert tryptophan into a range of metabolites, some of which support intestinal barrier function while others suppress inflammation in humans (Roager and Licht, 2018). If a bacterial community resides in the bloodstream, its members are also likely to closely interact with the host. However, it remains unclear how these interactions affect human health. Bacteria in blood was suggested to play a role in chronic inflammatory diseases such as Alzheimer’s disease (Potgieter *et al.*, 2015). Additionally, the presence of *Acinetobacter* *Baumannii* sequences in the blood of type II diabetic patients was positively correlated with levels of proinflammatory cytokines, and associated with chronic inflammation (Perera *et al.*, 2021). These findings suggest that bacterial residents in blood may play a role in human health and disease. If so, information about these interactions may be harnessed to develop microbiome-based therapeutics.

Further, the abundance of certain bacterial taxa in blood has been associated with health status. For example, *Klebsiella* and *Acinetobacter* were enriched in the blood of hepatocellular carcinoma patients (Cho *et al.*, 2019) while *Staphylococcus* was more abundant in celiac disease patients (Serena *et al.*, 2019). Such associations can be learnt by machine learning models for developing diagnostic tools. Additionally, these associations may be used to determine an individual’s predisposition to disease, or for predicting disease onset (*i.e.* prognosis). This would permit measures for disease prevention or early intervention.

## Limitations and suggestions

This study focused on contamination arising from reagents during library preparation and sequencing. However, contaminant microbial sequences may be introduced at any step along the process from sample collection to sequence. Ideally, appropriate negative controls for each sample processing step should be included. For example, Moriyama *et al.* (2008) used saline water exposed to povidone-iodine skin as a negative control for phlebotomy-associated contamination. Additionally, DNA extraction can be performed on skin-exposed saline water to control for extraction-associated contamination. Alternatively, sterile water can be used in place of blood during DNA extraction. Comparisons of microbial taxonomic profiles obtained from these different controls would allow us to track contamination introduced by the different sample processing steps. This then permits more stringent filtering of contaminant taxa from the observed taxonomic profiles for blood. Separately, other strategies to computationally reduce the effect of contamination on observed taxonomic profiles may be employed. For example, dilutions of blood samples with DNA-free water to yield samples with multiple DNA concentrations post-extraction could be performed. In such a study design, taxa whose observed relative abundance is inversely correlated to the sample DNA concentration can be considered contaminants (Jervis-Bardy *et al.*, 2015). Such alternative strategies can be used in tandem with the contamination analysis presented in this study for more stringent contaminant removal.

Another limitation of this study is the small sample size. The number of controls (*n* = 3) was much lower relative to blood samples (*n* = 23), resulting in highly unequal group sizes. Statistical tests are not meaningful in this context and were therefore avoided to prevent over-interpreting the data. While the addition of more negative controls would have permitted formal statistical testing, this was arguably unnecessary. Indeed, all analyses presented in this study, except that for rarefied genus richness, concordantly suggest an obvious difference between the microbial taxonomic profiles of the blood and control groups (**Figure 2**).

Separately, metagenomic sequencing measures the DNA molecules present and not live microbial cells. Cell-free DNA molecules entering the bloodstream from other bodily sites such as the mouth or gut may therefore be an alternative explanation for the taxonomic profiles observed in the blood samples. Additionally, even if the detected DNA sequences reflect the presence of live cells in blood, it remains unclear whether these microbial cells are transient or persistent. This is because the current study design offers only a snapshot of the microbial sequences present. Given these limitations, it must be stressed that further experimental validation is necessary to prove the existence of a hypothetical blood microbiome. One possible strategy is to probe the microbial mRNA profile in blood. For example, if metagenomic DNA sequencing identified *Escherichia coli* in blood, we expect to also observe *E. coli*-specific mRNA species. Concordance between DNA and RNA sequencing results therefore provides stronger evidence for an active microbial community in blood. Additionally, sequencing of blood samples from the same individuals across different time points (*i.e.* a longitudinal study) may shed light on the persistence of detected microorganisms. Such a study design also permits modelling of how the population numbers of microbial taxa changes with time, offering insight into their underlying ecological relationships and interactions (Faust and Raes, 2012). Agreement of these findings with known microbial interactions would provide additional evidence for an active community.

Finally, because the sequencing strategy used targets the 16S rRNA gene of bacteria, other infectious agents were not considered in the analysis. However, some of these infectious agents are likely to be important components of the blood microbiome. For example, at least 19 different viruses could be identified from the blood of 8,240 individuals (Moustafa *et al.*, 2017). Additionally, the torque teno virus was found in 70-100% of individuals sampled from ten regions across the world (Abe *et al.*, 1999). These findings suggest a remarkably high prevalence of viruses in human blood. Inclusion of viruses and other infectious agents in future studies will provide a more comprehensive view of the microorganisms present in the bloodstream.

In summary, the results suggest that the human bloodstream may harbour bacteria that do not necessarily lead to disease. Additionally, the use of *in silico* techniques to remove contaminants while retaining biologically relevant taxa after taxonomic profiling was demonstrated. The present findings challenge the existing paradigm that blood is sterile. Additionally, they lay the foundations for a more comprehensive understanding the full human microbiome, which may be harnessed in the long run to develop clinical prognostic tools or personalised therapeutics.

# Methods

## Sample collection

Phlebotomies were carried out on 13 female and 10 male volunteers (median age = 59). These individuals had no clinical symptoms of bloodstream infections and had normal levels of the C-reactive protein inflammatory marker. All volunteers were not undergoing antibiotic treatment prior to sample collection. Blood samples were collected in 4ml Vacutainer K3E (Becton Dickinson) tubes.

## DNA extraction

Microbial DNA was extracted from blood using the Blood Mini kit (A&A Biotechnology), as described previously (Gosiewski, Szała, *et al.*, 2014). The concentration and purity of extracted DNA was determined using NanoDrop (Thermo Scientific). Sterile water was used as a substitute for the extracted DNA in the negative water controls.

## 16S rRNA library preparation and sequencing

Paired-end sequencing of the hypervariable V3-V4 regions of 16S rRNA gene from extracted DNA was performed on the Illumina MiSeq System. Library preparation and sequencing was carried out in accordance with the manufacturer’s instructions (<https://tinyurl.com/ujr5j45b>). Briefly, the hypervariable V3-V4 regions were amplified via a nested polymerase chain reaction (PCR) procedure, as described previously (Gosiewski, Jurkiewicz-Badacz, *et al.*, 2014). PCR was carried out using the KAPA HiFi HotStart ReadyMix kit (KAPA BIOSYSTEMS) on a C100 thermal cycler (BioRad). The final DNA concentration of amplicon libraries for each sample was quantified using PicoGreen (Life Technologies). The libraries were then normalised to the same concentration and pooled to yield a single sequencing library. The sequences of all primers and adapters used are shown in Table 1. Sequencing was performed using the MiSeq Reagent Kit v3 (600 cycles) with a 20% PhiX spike-in as an internal control.

## **Sequencing read processing**

Raw sequencing reads were demultiplexed using bcl2fastq (v2.17.1.14; default parameters). Primers and sequencing adapters were removed, and low-quality bases at the start and end of reads were trimmed using *Cutadapt* (v2.6) (Martin, 2011). Read pairs were then merged using *ea-utils* (v1.1.2.779) (Aronesty, 2013). For read pairs where merging failed, only forward unmerged reads were retained. Reads with a Q-score below 20 removed using *BBMap* (v38.18) (Bushnell, 2014). Samples with less than 10,000 reads were excluded from further analysis. Read quality assessments before and after processing was performed using the *fastqcr* package (v0.1.2) (Andrews, 2010) in *R*.

## Taxonomic classification

*Kraken 2* (v2.0.7-beta; default parameters) (Wood, Lu and Langmead, 2019) was used to assign each processed read to a particular taxon based on the *Kraken 2*-built *SILVA* database (v138) (Quast *et al.*, 2012). All unclassified reads were excluded from the analyses. The taxonomic assignments for all reads were aggregated to generate a relative abundance matrix using a custom *Python* script written by Tan *et al.* (2020). In this matrix, samples are represented as rows and genera as columns. Each element equals the number of reads assigned to a particular genus for a single sample divided by the total number of reads for said sample.

## Microbial diversity

The rarefaction analysis of genus richness was performed using the *rarefy* function from the *Vegan* package (v2.5.7) in *R*. Rarefaction analysis of Shannon index was performed using a custom *R* script and the *diversity* function from the same package.

## Ordination and clustering

The Bray-Curtis distance matrix was computed from the relative abundance matrix using the *vegdist* function in *Vegan*. PCoA, *t*-SNE and *k*-means was computed using the *pcoa*, *Rtsne* and *kmeans* functions in the *ape* (v5.4.1) (Paradis and Schliep, 2019), *Rtsne* (v0.15) (Krijthe, van der Maaten and Krijthe, 2018) and *stats* (v3.6.0) packages in *R*, respectively. The Barnes-Hut implementation of *t*-SNE (Van Der Maaten, 2014) was used with the perplexity parameter set to two. The ‘centers’ and ‘nstart’ parameters in *kmeans* was set to three and 25 respectively.

## Relative differential abundance

As suggested previously (Morton *et al.*, 2019), RDA was computed using the equation, , where *xtarget*and *xreference* is the relative abundance of the genus in question and the reference genus, respectively. *Bradyrhizobium* was selected as the reference genus since it is the most common sequencing contaminant in metagenomic sequencing studies (Laurence, Hatzis and Brash, 2014) and therefore not likely to be part of the blood microbiome. This is important because the RDA of a reference taxon always equals one and therefore cannot be interpreted meaningfully.

# Data and code availability

All analyses or data processing was performed in *R* v3.6.0 or *Python* v3.6.13. Relevant source code is hosted on GitHub (<https://github.com/cednotsed/BIOC0023_dissertation>). The raw sequence data for this study was obtained from the study by Gosiewski *et al.* (2017).

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