Life history recorded in the vagino-cervical microbiome

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SUMMARY

The vagina contains at least a billion microbial cells, which are dominated by Lactobacilli. Here we perform metagenomic shotgun sequencing on cervical samples from 1148 women. Factors such as pregnancy, delivery histories and breast-feeding were all more important than menstrual cycle in shaping the microbiome. *Bifidobacterium breve* was seen with older age at sexual debut; *Lactobacillus crispatus* negatively correlated with pregnancy history; potential markers for lack of menstrual regularity, heavy flow, dysmenorrhea, contraceptives were also identified. Other features such as mood fluctuations and facial speckles could potentially be deduced from the vagino-cervical microbiome. Gut and oral microbiome, plasma vitamins, metals, amino acids and hormones showed associations with the vagino-cervical microbiome. Our results offer an unprecedented glimpse into the microbiota of the female reproductive tract and call for international collaborations to better understand its long-term health impact.

Highlights:

Shotgun sequencing of 1148 vagino-cervical samples reveal subtypes;

Other omics such as moods and skin features could be predicted by the vagino-cervical

bacteria;

Factors such as delivery mode and breast-feeding associate with the vagino-cervical

microbiome;

With dwindled Lactobacilli, postmenopausal samples are relatively enriched for viruses.

INTRODUCTION

The human body is a supra-organism containing tens of trillions of microbial cells

(Sender et al., 2016). Studies in human cohorts and animal models have revealed an

integral role played by the gut microbiota in metabolic and immunological functions

(Sommer and Bäckhed, 2013). Disease markers as well as prebiotic or probiotic

interventions are being actively developed (O'Toole et al., 2017; Wang and Jia, 2016).

Studies on other mucosal sites such as the vagina and the mouth lag behind (Lloyd-

Price et al., 2017; The Human Microbiome Project Consortium., 2012; Zhang et al.,

2015b); the potential for the microbiota in these body sites has not been fully realized.

The presence of microorganisms beyond the cervix (i.e. the upper reproductive tract) is

increasingly recognized even in non-infectious conditions (Aagaard et al., 2014; Chen et

al., 2017; Li et al., 2018), with much debated implications for women's and infants'

health.

Lactobacilli have long been regarded as the keystone species of the vaginal microbiota.

Lactic acid produced by these microorganisms helps maintain a low vaginal pH of 3.5-

4.5, and wards off pathogenic micro-organisms (Ma et al., 2012). Prevention of the

human immunodeficiency virus (HIV) and other sexually transmitted infections (STIs),

preterm birth and bacterial vaginosis (BV) has been a major effort. Germ-free mice

treated with *L. crispatus* had fewer activated CD4+ T cells in the genital tract compared

to those treated with *Prevotella bivia*, explaining the difference in HIV acquisition in

human cohorts (Gosmann et al., 2017). How vaginal Lactobacilli interplay with *Candida*

albicans and other related fungi is also an important question for preventing or treating

vulvovaginal candidiasis (Bradford and Ravel, 2017). The over 90% of human

sequences in female reproductive tract samples, in contrast to 1% in feces (Li et al.,

2018; Methé et al., 2012; Wang and Jia, 2016), has made metagenomic shotgun

sequencing more expensive. Most studies of the vaginal microbiota used 16S rRNA

gene amplicon sequencing, which lacked a view of the overall microorganism

communities including bacteria, archaea, viruses and fungi (Byrd et al., 2018), as well

as the functional capacity encoded. Besides infection, studies on current sexual activity

and the menstrual cycle occurred naturally to the vaginal microbiota field (Gajer et al.,

2012; Ravel et al., 2010). However, lasting impacts from other potentially important

factors such as sexual debut, pregnancy and breast-feeding have not been looked at in

a reasonably large cohort.

As a sizable reservoir of microbes instead of a transient entity, the female reproductive

tract microbiota might also reflect conditions in other body sites. It is however not clear

whether other omics in circulation or in the intestine cross-talks with the vagino-cervical

microbiome. Intersecting with hormones, metabolic and immune functions, we find it

intriguing to explore the potential link of the vagino-cervical microbiome to the brain and

the face.

Here, we report the full spectrum of the vagino-cervical microbiome from 1148 healthy

women using metagenomic shotgun sequencing. As part of the 4D-SZ (trans-omic, with

more time points in future studies, based in China) cohort, we also comprehensively

measured parameters such as fecal/oral microbiome, plasma metabolites, medical test

data, immune indices, physical fitness test, facial skin imaging, as well as female life

history questionnaire, lifestyle questionnaire, and psychological questionnaire (Figure 1).

Our work pinpoints other metadata or omics that can predict or be predicted from the

microbiota in the female reproductive tract, which would illuminate future designs of

population cohorts, mechanistic investigations, as well as means of intervention.

RESULTS

Dominant bacterial and non-bacterial members of the vagino-cervical
metagenome

To explore the vagino-cervical microbiome, 516 healthy Chinese women aged 21-52

(median 29, 95% CI: 23–39) were recruited during a physical examination as the initial

study cohort (Figure 1; Table S1A). Metagenomic shotgun sequencing was performed

on the cervical samples, and high-quality non-human reads were used for taxonomic

profiling of the vagino-cervical microbiome (Figure 2A; Table S1B).

In agreement with 16S rRNA gene amplicon sequencing data from the US (Ravel et al.,

2010), the vagino-cervical microbiota of this Asian cohort was mostly Lactobacilli-

dominated, while 19.19% of women harbored over 50% *Gardnerella vaginalis* (Figure

2A, Figure S1A). Although *A. vaginae* and *G. vaginalis* were commonly believed to co-

occur in bacterial vaginosis (BV) (Fredricks et al., 2005; Serrano et al., 2019), 4 of the

10 volunteers with >50% in their cervical samples appeared to have no *G. vaginalis*

(Figure 2A). The groups showed different characteristics in other omics (Figure 2B-O,

Generalized linear model (GLM), p <0.05). 22.67% of the cohort was dominated by

Lactobacillus iners (Figure 2A, Figure S1A), which was far less protective against

bacterial and viral infections compared to *Lactobacillus crispatus* (Gosmann et al., 2017;

Petricevic et al., 2014). The type characterized by *L. crispatus* was overrepresented in

the women who had fewer pregnancies (Figure 2C, 2D). The plasma concentrations of

17α-hydroxyprogesterone and aldosterone were higher in individuals of the *L. crispatus*-

type than in *G. vaginalis* type individuals (Figure 2H-2J, p <0.05). Rare subtypes (> 50%

relative abundance in less than 5% of the individuals) such as *Bifidobacterium breve*

(3.29%)*, Lactobacillus jensenii* (2.91%)*, Lactobacillus gasseri* (2.91%)*, Atopobium*

vaginae (2.31%)*, Lactobacillus johnsonii* (1.55%)*, Streptococcus anginosis* (1.36%)*,*

and Clamydia trachomatis (1.16%) were also detected in this cohort (Figure 2A, Figure

S1A). Individuals dominated by *B. breve* had older age at vaginal sexual debut

compared to those dominated by *L. cripspatus* or *L. iners* (Figure 2B, p = 0.00026 and p

= 0.0019, respectively). *Streptococcus agalactiae* (Group B *Streptococcus*), a bacterium

responsible for neonatal sepsis and recently reported in placenta (de Goffau et al.,

2019), could be detected in 5.62 % of the individuals (Figure 2A, Table S1C). Other

microorganisms including *Prevotella bivia*, *Escherichia coli*, *Ureaplasma parvum*,

human papillomavirus (HPV), herpesviruses, Influenza A virus and *Haemophilus*

influenzae were abundant in some individuals (Figure 2A, Table S1C). According to the

metagenomic data, the mean proportion of non-bacterial sequences was 3.45% (Figure

2A). The vaginal types (> 50% relative abundance for the single bacterium) of *G.*

vaginalis, *L. crispatus*, and *B. breve* showed lower proportions of human sequences

than other types (e.g. p = 3.9e-6 between *L. crispatus* and *L. iners* types, p = 1.7e-8

between *G. vaginalis* and *L. iners* types, p = 0.0036 between *B. breve* and *L. gasseri,*

Wilcoxon ranked sum test, Figure S1B), suggesting that in future studies lower amounts

of sequencing could be used for these compared to other types.

101   Factors shaping the vagino-cervical microbiome and beyond

We computed the prediction value (5-fold cross-validated random forest model) of each

factor in the female life history questionnaire on the microbiome data independently,

and found the most important factors to be pregnancy history, marriage, number of

pregnancies, number of vaginal deliveries, age at vaginal sexual debut, followed by age

of marriage, current breast-feeding, and number of caesarean sections (Figure 3, 999

permutations and Benjamini-Hochberg tests, $q < 0.05$). Number of pregnancies

correlated with pregnancy history (Spearman's correlation coefficient (cc) = 0.916) and

with number of abortions (Spearman's cc = 0.699); Age at first pregnancy correlated

age at most recent pregnancy (Spearman's cc = 0.636).

These important factors were validated in an independent cohort of 632 individuals that

differed in age distribution as well as sequencing mode (Figure 1, Figure S2, Table S1E,

paired-end 100bp for vagino-cervical samples). Questionnaire entries such as

pregnancy history, marital status, current breast-feeding, and mode of the most recent

delivery were again found as the most important factors to influence the vagino-cervical

microbiome (Figure S2). The strong signal with duration of current breast-feeding

reflected difference in questionnaire design that was only available in one but not the

other cohort (Figure 4, Table S1A, Table S1E), while the impact from menstrual cycle

was partly augmented with the presence of postmenopausal women in the second

cohort (Figure 3, Figure S2).

45 of the volunteers in the second cohort were postmenopausal (median age 54, 95%

CI: 52-55), an age group untouched by HMP. Metagenomic shotgun data revealed

diminished Lactobacilli in their vagino-cervical microbiome, while the mean proportion of

viral sequences reached 37% (Figure S3). HPV was not the most abundant or prevalent

virus in these postmenopausal individuals; a diverse range of viruses named after plant

or animal hosts could be detected. In contrast, there was no sign of fungal boom. The

non-Lactobacilli bacterial species were also known as vaginal or oral species, with

overgrowth of *Escherichia* in only 2% of the individuals (Figure S3C).The taxonomic

profile remained robust when we arbitrarily trimmed the paired-end 100bp data to

single-end 50bp or single-end 100bp (Spearman's correlation coefficient = 0.998

between Pseudo-SE50 and Pseudo-SE100, 0.993 between Pseudo-SE50 and PE100,

Figure S4).

As a whole, the vagino-cervical microbial composition showed the greatest explained

variances for these questionnaire data collected for the female reproductive tract

samples, followed by other data collected on the same day, such as fecal microbiome

composition, psychological questionnaire, plasma metabolites, immune indices, facial

skin imaging and medical test data (Figure 5A). *L. crispatus* in the fecal microbiome was

most predictive of the vagino-cervical microbiome, and plasma phosphoserine, L-

homocitrulline, testosterone were ranked at the top among metabolites (largest

Spearman's cc between RVCV prediction and observed data, and p < 0.01 with 999

permutations, Figure 5B), while weaker signals were observed for self-assessed mental

status, and pores on the cheeks (p < 0.05 but q > 0.1, Figure 5B).

Specific influences from pregnancy histories, contraception and menstrual
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symptoms

Marital status was one of the most significant factors to influence the vagino-cervical

microbiome (Figure 3, Figure S2). It showed negative correlations with relative

abundances of *L. crispatus* (Spearman's correlation, q value=1.71E-08), *Acinetobacter*

species (q value=5.02E-07), *L. jensenii* (q value=0.0001), *L. vaginalis* (q

value=0.000086), and *Ureaplasma parvum* (q value=0.012) and positive correlation with

Bifidobacterium breve (q value=0.0818) (Figure 6A, Table S3). Compared to unmarried

women, married women had higher concentrations of plasma 25-hydroxy vitamin D, and

their plasma testosterone (responsible for sexual drive), dehydroepiandrosterone

(DHEA), and creatinine had declined (Figure 6A). The age at vaginal sexual debut

showed positive correlations with *Gardnerella vaginalis* and *Scardovia* species, and

negative associations with *L. crispatus* and *L. iners* (Figure 6B, Table S3).

Similarly, the women who went through pregnancy showed relatively less *Lactobacillus*

compared to nullipara, including *L. crispatus*, *L. vaginalis*, and *L. jensenii*, but were

enriched for *Actinobacteria*, *Bifidobacteriaceae*, *Anelloviridae* and *Torque teno* virus (the

most abundant anellovirus in the human virome) in the vagino-cervical microbiome

(Figure 6C, Table S3, Figure S5). We observed increased concentrations of plasma

vitamin D, blood glucose and direct bilirubin in women with previous pregnancy, but

lower concentrations of plasma testosterone, androstenedione, dehydroepiandrosterone

and methionine (Figure 6C). Vaginal deliveries were associated with decreased *L.*

crispatus, *L. jensenii*, *Bartonella* species, *Prevotella timonensis*, and increased

Lactobacillus sp. 7_1_47FAA (Figure 6D, Table S3). We observed a lower relative

abundance of *Ureaplasma parvum* in individuals who delivered by cesarean section

(Figure 6E, Table S3), a bacterium commonly isolated from pregnant women (Anderson

et al., 2013) and recently reported in the lower respiratory tract of preterm infants

(Pattaroni et al., 2018) and in preterm placenta (de Goffau et al., 2019). Compared with

vaginal deliveries, the plasma concentrations of testosterone, androstenedione,

methionine, threonine and tryptophan were significantly lower in women who

experienced caesarean section (Figure 6D, 6E). In addition, these women more often

suffered from an abnormal leucorrhoea (Figure 6E).

63 volunteers in our initial cohort and 74 in the second cohort happened to be actively

breast-feeding. *L. crispatus* type which abundance >50% was found to be less (5.8%) in

these actively breast-feeding individuals, in contrast to *G. vaginalis* type which was

found in 25.5% of these individuals (Figure 6F, Figure 4). Alkaline phosphatase, plasma

vitamin D and lead (Pb) were found to be more abundant in the breast-feeding

individuals, consistent with slight reduction of progesterone and creatinine levels in

lactating women (Figure 6F). Gravida and para, especially deliveries by caesarean

section, appeared associated with lower facial skin score ranking in population such as

UV spots and porphyrins, but these problems were less pronounced in caesarean

section mothers with breast-feeding (Figure 6C-6F).

We found multiple significant associations between the contraceptive methods of

participants and their vagino-cervical microbiome. Condom usage showed negative

correlations with *L. iners* and *Comamonas* species, and positive associations with *L.*

gasseri (Table S2, Figure 7, Table S3). Oral contraceptives, although still rare in our

cohort, were associated with increased *Ureaplasma parvum and Comamonas* species

(Table S2, Figure 6G, Table S3, and Figure 7). *Comamonas* has been implicated in

fecundity in *C. elegans* and identified as a marker for infertility due to endometriosis

(Chen et al., 2017; MacNeil et al., 2013). *Comamonas testosteroni* TA441 is known to

degrade testosterone (Horinouchi et al., 2003). Moreover, oral contraceptives exhibited

a positive correlation with plasma homocitrulline, and as yet not significant declines in

mental health and butyrate-producing fecal microbiota species such as

Faecalibacterium prausnizi and *Roseburia intestinalis* (Figure 6G), which could

potentially contribute to the known side effect of oral contraceptives in cardiovascular

risk. Thus, although lack of contraception could lead to infection, none of the

contraceptive methods appeared healthy for the microbiome in the long run.

Menstrual phases are known to influence the microbiota in the female reproductive tract

(Chen et al., 2017; Gajer et al., 2012). We confirmed in our cohort the shift in *L.*

crispatus and *L. iners* during menstrual cycle, coinciding with dynamics in progesterone

as well as threonine and arginine (Figure 6H, Figure S6). White blood cell counts (WBC)

also recovered after menses, consistent with greatest susceptibility to infection at the

onset of menses. *L. vaginalis*, *L. johnsonii* and *Weissella* species showed negative

correlations with self-reported regular periods (Figure 7). *Propionibacterium acnes* and

Dialister micraerophilus were positively associated with a heavier flow (Figure 7, Table

S3). Many women experience dysmenorrhea during menses (No: n=84, Slight: n=360,

Serious: n=68, Table S1A). Individuals with dysmenorrhea were enriched for

Pseudomonadales, *Acinetobacter* and *Moraxellaceae*, while lower in plasma level of

histidine (Figure 6I), consistent with these bacteria encoding histidine decarboxylases to

convert histidine into histamine (Cundell et al., 1991).

Association between omics

Integrated association network using a wisdom of crowds approach (Marbach et al.,

2012) also revealed interesting patterns (Spearman's correlation, random forest and

linear regression, with arcsin sqrt-transform for the microbiome profiles, Figure 7, Table

S3). The relative abundance of *G. vaginalis* negatively associated with sleep and

appetite, and mental state, while positively associated with plasma levels of mercury

(Hg) and vitamin E (Figure 7, Table S3). *L. iners* negatively correlated with times of

spontaneous abortion, days since last menstrual bleeding, condom usage and the

plasma concentration of vitamin D and vitamin A, and positively correlated with plasma

concentrations of hemoglobin, and alanine. In addition, vaccination history, such as

those against HPV may be associated with higher relative abundance of *L. iners* (Figure

7, Table S3).

While lacking significant association with the vagino-cervical microbial composition, the

immune repertoire data, especially TRBV7.3 and TRBV7.4, showed multiple

associations with functional pathways in the vagino-cervical microbiome, such as purine

and pyrimidine metabolism, synthesis of branched-chain amino acids, histidine and

arginine (Figure S7). Red blood cell counts, plasma vitamin A and plasma hydroxyl

vitamin D levels negatively associated with CDP-diacylglycerol biosynthesis pathways,

consistent with presence of diacylglycerol kinase in Lactobacilli with anti-inflammatory

functions (Andrada et al., 2017; Ganesh et al., 2017). Fecal *Coprococcus comes*, a

bacterium previously reported to associate with cytokine response to *Candida albicans*

(Schirmer et al., 2016), was seen here to associate with isoleucine pathways in the

vagino-cervical microbiome (Figure S7).

The second cohort had saliva metagenomics data (Figure 1), which allowed us to

explore the oral microbiome, a site that was reported to show similarity to the placenta

microbiome (Aagaard et al., 2014). Associations with the vagino-cervical microbiome

could be observed (Table S4). Oral human herpesvirus was positively correlated with

Bifidobacteriaceae and *G. vaginalis* in vagina. *Scardovia wiggsiae*, a bacterium

previously reported to associate with early childhood caries, showed positive correlation

with vaginal *Staphylococcus* species. Oral *Treponema lecithinolyticum* showed positive

correlation with *Dialister micraerophilus*.

We next analyzed the integrated association network between omics in the second

cohort (Figure S8), and patterns consistent with the initial cohort could be identified

(Table S4B). Pregnancy history, current breast-feeding showed negative correlations

with relative abundances of *L. crispatus*, *L. jensenii*, *L. vaginalis*, *L. iners* and *U. parvum*.

We also reconfirmed a lower relative abundance of *U. parvum* and a higher abundance

of *P. timonensis* in individuals who delivered by cesarean section, while individuals with

past vaginal deliveries showed a lower relative abundance of *P. disiens, P. timonensis,*

P. buccalis and *Finegoldia magna* (Table S4B, q<0.1). Higher concentrations of

dehydroepiandrosterone, testosterone were observed in women with higher abundance

of *L. crispatus. Finegoldia magna* negatively correlated with Vitamin B1. *Peptoniphilus*

harei negatively correlated with testosterone. *P. bivia* negatively correlated with

progesterone. We observed higher concentrations of threonine, arginine, and serine, in

women with higher abundance of *U. parvum*, *A. vaginae* and *G. vaginalis* positively

correlated with the red blood cell (RBC). *Finegoldia magna* and *Peptoniphilus harei*

positively correlated with the urine specific gravity, used in the evaluation of kidney

function*. L. crispatus* show the strongest positive correlation with gut microbe. The BV

species *P. bivia* negatively associated with fecal *Butyricimonas* species and *Clostridia*

species, while positively associated with fecal *P. bivia*, suggesting a fecal reservoir for

recurrent vaginal infections. *P. disiens, P. buccalis* and *P. timonensis* negatively

associated with physical fitness test score (Figure S8). The wrinkles and red area in

forehead were relieved in individuals who enriched for *L. iners*. Together, these results

confirmed the long-range links between the vagino-cervical microbiome and other body

sites.

DISCUSSION

As the largest metagenomic study for the vagino-cervical microbiome, our data revealed lesser known subtypes for the vaginal microbiota, and put into context viral and fungal sequences present in healthy women. Our multi-omic data could help target efforts aimed at promoting a healthy reproductive tract microbiota and offering better advices for mothers from pregnancy to recovery, as well as preventing infections from viruses such as HIV and HPV. For example, whether vitamin D supplementation should be considered in African countries to reduce vaginal *L. iners* or rise *L. crispatus*, as was tried recently in a pregnant cohort (Jefferson et al., 2019). Gut probiotics such as *L. casei*, *B. longum* have been reported to increase vitamin D in ovariectomy-induced mice model of osteoporosis (Montazeri-Najafabady et al., 2018), and our results suggest that there might be counterparts in the female reproductive tract after getting married and pregnant.

Recent publications from iHMP (integrative Human Microbiome Project) provided longitudinal data during pregnancy and showed relatively more *L. iners* compared to non-pregnant individuals even in women of African American history (DiGiulio et al., 2015; Fettweis et al., 2019; Petricevic et al., 2014; Serrano et al., 2019). In our data, the *L. iners* versus *L. crispatus* shift was apparent in women with past pregnancy, and *L. iners* interestingly showed a negative association with number of spontaneous abortions (Figure 7). *L. iners* and other Lactobacilli have been detected in the placenta (Aagaard et al., 2014; de Goffau et al., 2019; Lannon et al., 2019; Macklaim et al., 2011; Seferovic et al., 2019), amniotic fluid, nasal and pharyngeal sites (Boeck et al.; Wang et al., 2018a). Aldosterone, a major mineralocorticoid for which we observe association with

potentially beneficial bacteria in the gut microbiome in an accompanying study (Jie et al.,

2019), positively associated with *L. crispatus* in the vagino-cervical microbiome, while a

precursor for aldosterone, corticosterone, positively associated with *L. iners* (Figure 7).

How vitamin D and hormone metabolism might impact the vagino-cervical microbiome

would require further studies. How the uterus and the microbiome recover during

breastfeeding is also of interest for both the mother and future children (Anton et al.,

2018; DiGiulio et al., 2015). *S. anginosus*, has been shown to be more abundant in the

gut microbiome of individuals with atherosclerotic cardiovascular diseases (Jie et al.,

2017), and here we see young women who harbored > 50% *S. anginosus* in cervical

samples showing higher plasma creatinine and lower 17α -hydroxyprogesterone, which

might relate to preterm birth (de Goffau et al., 2019). The vagino-cervical microbiome of

postmenopausal women revealed a myriad of viral and bacterial species. While fungal

growth might be unfavorable both due to high pH and lack of glycans. While the focus in

the field has always been infection, our data highlight major aspects that are worth

further investigations for women in the modern world.

While samples from multiple body sites (peritoneal fluid from the pouch of Douglas,

fallopian tubes, endometrium, cervical mucus and two vaginal sites) were taken from

volunteers with benign conditions such as hysteromyoma, adenomyosis and

endometriosis (Chen et al., 2017; Li et al., 2018), we were only able to sample the

vagino-cervical microbiome in this healthy cohort. Interestingly, our cohort generally

lacked bacteria known for BV (e.g. (Fettweis et al., 2019; Serrano et al., 2019).) and

also contained less *Prevotella* compared to some of the surgically sampled individuals.

In the postmenopausal samples, some of the bacteria previously reported in the upper

reproductive tract (Chen et al., 2017; Lee et al., 2019; Li et al., 2018) and involved in

degradation of hormones (Wang et al., 2018b), e.g. *Pseudomonas* spp. could be seen

in the vagino-cervical microbiome, while disease relevance such as *A.*

vaginae and *Porphyromonas* in endometrial cancer would require more evidence

(Walther-António et al., 2016)..

By reaching to the cervix with a cytobrush, reflecting both the upper and the lower

reproductive tract (Chen et al., 2017; Li et al., 2018), we show here that the association

with the fecal microbiome was scarce overall, and the notion of reservoirs in the

intestine or other sites for vaginocervical bacteria (Marrazzo et al., 2012) would need

further investigation, especially in light of individual differences in the number of CD4+ T

cells in mucosal sites (Gosmann et al., 2017). There were other interesting associations

between different species that potentially involve immune modulation (Fig. 7). The

plasma metabolites and T cell receptor types associated with the vagino-cervical

microbiome are distinct from those associated with the fecal microbiome (Jie et al.,

2019). Vaginal *Prevotella* could induce more CD4+ T cells (Gosmann et al., 2017), but

the *Prevotella* species are not the dominant gut species of *Prevotella copri* which may

compete with *Bacteroides* spp. (Jie et al., 2017). The vagino-cervical microbiome also

better predicted facial skin features compared to the fecal microbiome (Jie et al., 2019),

perhaps due to a clearer pattern of hormone and immune signatures. The associations

with physical fitness tests and self-reported physical activities were however less

prominent in the vagino-cervical compared to the fecal microbiome (Jie et al., 2019), as

the changes due to pregnancy, delivery and breastfeeding may not be easily modifiable

with physical activity. As a densely populated microbiota other than the distal gut, the

vagino-cervical microbiota has the potential to reflect or even influence physiology

elsewhere in the human body.

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Supplemental Information includes six figures and five tables and can be found with this

article online at XXX.

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AUTHOR CONTRIBUTIONS

H.J. and C.C. conceived and organized this study. J.W. initiated the overall health

project. C.C., L.H., F.L, L.S., Y.L., X.Y. and N.L. performed the sample collection and

questionnaire collection. X.T., Y.K., W.R., Y.L., D.Z., X.Q., X.C., and J.Z. provided the

omics data. Z.J., C.C., F.L, L.H., and L.T. performed the bioinformatic analyses, H.J.,

C.C., Z.J. and X.Z. wrote the manuscript. All authors contributed to data and texts in this

manuscript.

DECLARATION OF INTERESTS

407 The authors declare no competing financial interest.

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FIGURE LEGENDS

Figure 1. Schematic overview of the study.

The study consists two cohorts with varying characteristics. 516 volunteers recruited in

2017 are regarded as the initial study cohort. A second cohort containing 632 volunteers

were recruited in 2018. Vagino-cervical microbiome, fecal microbiome, metabolites,

medical test data, physical fitness test data, facial skin feature and three kinds of

questionnaires are collected in both cohorts. Saliva microbiome is only available in the

second cohort and the woman life questionnaires differ by a few terms.

Figure 2. Vagino-cervical microbiome of the initial study cohort.

(A) The microbial composition in each sample at the species level according to

MetaPhlAn2 is shown. The samples were hierarchically clustered (R base hcluster

function with centroid linkage based on Euclidean distance. Black and blue taxa labels

used in legend denote bacteria and viruses, respectively.

(B-O) Specific omics factors that shows significant difference among 14 key vaginal

microbiota types estimated by GLM likelihood ratio test ($p<0.05$, 554 comparisons). T

test use for post hoc compare. RA stands for relative abundance. The genus in sub-

figure (M), (N), (O), (P) belongs to fecal microbiome. Boxes denote the interquartile

range (IQR) between the first and third quartiles (25th and 75th percentiles,

respectively), and the line inside the boxes denote the median. The whiskers denote the

lowest and highest values within 1.5 times the IQR from the first and third quartiles,

respectively.

Figure 3. Factors from female life history questionnaire influencing the vagino-

cervical microbiome in the initial study cohort.

Female life history questionnaire entries on the vagino-cervical microbiome, ordered according to their 5-fold cross-validated random forest (RFCV) importance on the microbiome composition. X-axis (length of the bar) is the model performance measured as the spearman's correlation between the prediction and measurement. First column stars after y-axis label are 999 times permutation p-value, second column stars are BH adjust p-value (32 comparisons), an "**+**" denotes Q-value <0.1, an asterisk denotes Q-value <0.05, two asterisks denote Q-value <0.01, three asterisks denote Q-value <0.001**.**

Figure 4. Vagino-cervical microbiome of 137 current breastfeeding women from two cohorts.

The microbial composition in each sample at the species level (A) and kingdom level (B) according to MetaPhlAn2 is shown. The dendrogram in (A) was a result of a centroid linage hierarchical clustering based on Euclidean distances between the microbial composition proportion. The bottom portion of the (A) illustrates months of breastfeeding by the time of sampling for each subject and the source of each sample, and the max marked by red which is 40 months in the bar. Due to months of breastfeeding is only available in the second cohort, the grey bars mean lack of this data. The red, black and blue labels used in legend denote kingdom, bacteria, and viruses, respectively.

Figure 5. Global view of factors influencing the vagino-cervical microbiome in the initial study cohort.

(A) Predicting the vagino-cervical microbiome from each omics and vice versa using stepwise redundancy analysis. Numbers on the straight arrows indicate adjusted R-

squared from vagino-cervical microbiome to omics data; numbers on the curved arrows

indicate adjusted R-squared from omics data to vagino-cervical microbiome. (B) Top 8

factors in each type of omics that are predicted by the vagino-cervical microbiome. The

length of the bars represents RFCV Rcorrelation coefficient between the actual

measurements and the values predicted by 5-fold cross-validated random forest models.

First column stars after y-axis label are 999 times permutation p-value, second column

stars are BH adjust p-value within each omics (4308 comparisons), an "+" denotes Q-

value <0.1, an asterisk denotes Q-value <0.05, two asterisks denote Q-value <0.01,

three asterisks denote Q-value <0.001.

Figure 6. Specific influences from reproductive factors on omics data in the

initial study cohort.

The factors shown ((A) Marriage; (B) Age at vaginal sexual debut; (C) Pregnancy

history; (D) Number of vaginal deliveries; (E) Number of cesarean deliveries; (F) Current

breast-feeding; (G) Oral contraceptives; (H) Days since last menstrual bleeding; (I)

Dysmenorrhea). The bars are colored according to the type of omics, as in **Figure 3**The

metabolites such as amino acids, hormones and vitamins are measured in plasma, and

trace elements are measured in whole blood. The blood biochemistry such as alkaline

phosphatase, fasting blood sugar, direct bilirubin, creatinine, total bilirubin, high-density

lipoprotein is measured in serum. The length of the bars represents Spearman's

correlation coefficient between the factor and the omics data. A plus sign denotes BH-

adjusted P-value <0.1 within each omics (average rank selects 13425 edges from

66301 associations, 523 edges for vagino-cervical microbiome, 11775 for fecal

microbiome, 321 for metabolites, 280 for medical test, 70 for physical fitness test, 137

for facial skin feature, 319 for lifestyle questionnaire), an asterisk denotes Q-value <0.05,

two asterisks denote Q-value <0.01, three asterisks denote Q-value <0.001, four

asterisks denote Q-value <0.0001, and five asterisks denote Q-value <0.00001.

Figure 7. Wisdom of the crowds for the association network between vagino-

cervical microbial species and other omics data in the initial study cohort.

Results from generalized linear model with penalty (cv. glmnet), random forest (RFCV)

and Spearman's correlation are integrated and then visualized in CytoScape. Red lines,

negative associations; cyan lines, positive associations (23385 are vagino-cervical

microbiome and other omics, among them, 878 for metabolites, 785 for medical test,

216 for physical fitness test, 392 for facial skin feature, 162 for psychological

questionnaire, 1096 for lifestyle questionnaire, 19856 for fecal microbiome, adding

66301 edges from female life history questionnaire and other omics, total 89828

associations).

STAR★METHODS

KEY RESOURCES TABLE

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Biological Samples		
Cervical samples	This paper	N/A
Fecal samples	This paper	N/A
Saliva samples	This paper	N/A
Blood samples	This paper	N/A
Critical Commercial Assays		
FTA card	BGI	N/A
MGIEasy sample collection kit	MGI	http://www.mgitech.cn/article/det
MGIEasy DNA Library Prep Kit	MGI	http://www.mgitech.cn/article/det
Deposited Data		
Raw sequencing data	This paper	CNGB database accession CNP
Software and Algorithms		
Metaphlan2	Nicola Segata et al., 2012	https://bitbucket.org/biobakery/m
R	R Development Core Team	https://www.r-project.org/
randomForest R package	A. Liaw and M. Wiener et al., 2002	https://CRAN.R-project.org/pack
packfor R package	N/A	https://rdrr.io/rforge/packfor/
CytoScape	Paul Shannon et al., 2003	https://cytoscape.org/
glmnet R package	Robert Tibshirani et al., 2010	https://CRAN.R-project.org/pack
ggplot2 R package	H. Wickham et al., 2016	https://CRAN.R-project.org/pack
HUMANn2	Huttenhower C et al., 2018	https://bitbucket.org/biobakery/hu
pheatmap R package	N/A	https://CRAN.R-project.org/pack

CONTACT FOR REAGENT AND RESOURCE SHARING

Further information and requests for resources and reagents should be directed to, and

will fulfilled by, the Lead Contact, Huijue Jia (jiahuijue@genomics.cn).

EXPERIMENTAL MODEL AND SUBJECT DETAILS

Initial Study Cohort

As the first time point for the vagino-cervical microbiome of the 4D-SZ cohort, 516

volunteers joined between May 2017 and July 2017 during an annual physical

examination. Baseline characteristics of the cohort are shown in Table S1A.

The study was approved by the Institutional Review Boards (IRB) at BGI-Shenzhen,

and all participants provided written informed consent at enrolment.

The Second Cohort

An independent cohort of 632 were also recruited between May 2018 and July 2018.

2018 data for 4D-SZ volunteers who were already included in the initial cohort would be

published in a future study. The process of omics data collection was consistent with the

initial cohort. In addition, saliva samples were collected only in this cohort. Baseline

characteristics of the cohort are shown in Table S1E.

The study was approved by the Institutional Review Boards (IRB) at BGI-Shenzhen,

and all participants provided written informed consent before any material was taken.

METHODS DETAILS

Demographic Data Collection

During physical examination, the volunteers received three kinds of online questionnaire.

The female life history questionnaire contained pregnancy and delivery history,

menstrual phases, sexual activity, contraceptive methods. The lifestyle questionnaire

contained age, disease history, eating and exercise habits. The psychological

questionnaire contained the evaluation of irritability, dizziness, frustration, fear, appetite,

self-confidence, resilience (Table S1A, S1E).

Samples Collection

Cervical samples were collected and smeared in the Flinders Technology Associates

(FTA) cards by the doctor during gynecological examination. Fecal samples and saliva

samples were self-collected by volunteers. Cervical samples, fecal samples and saliva

samples were stored for metagenomic shotgun sequencing. The overnight fasting blood

samples were drawn from a cubital vein of volunteers by the doctors.

DNA extraction and metagenomic shotgun sequencing

DNA extraction of cervical samples and fecal samples was performed as described

(Chen et al., 2017; Li et al., 2014). Metagenomic sequencing was done on the BGISEQ-

500 platform, which is highly comparable to Illumina HiSeq platforms in metagenomic

and other sequencing applications (Fang et al., 2018; Han et al., 2018; Li et al., 2018;

Pan et al., 2018). 50bp of singled-end reads for cervical samples collected in the initial

study cohort, and on average 208.76 million raw reads were sequenced for each

sample (Table S1B); 100bp of singled-end reads for fecal samples collected in the initial

study cohort, and on average 85.63 million raw reads were sequenced for each sample

(Table S1B); 100bp of paired-end reads for cervical samples, fecal samples and saliva

sample collected in the second cohort, and on average 158.91 million raw reads, 75.84

million raw reads were sequenced for each cervical sample and saliva sample,

respectively (Table S1B). Quality control and alignment to GRCh38 was performed as

previously described (Fang et al., 2018; Li et al., 2018).

UHPLC-MS quantification of amino acids

40 µl plasma was deproteinized with 20 µl 10% (w/v) sulfosalicylic acid (Sigma)

containing internal standards, then 120 µl aqueous solution was added. After

centrifuged, the supernatant was used for analysis. The analysis was performed by ultra

high pressure liquid chromatography (UHPLC) coupled to an AB Sciex Qtrap 5500

mass spectrometry (AB Sciex, US) with the electrospray ionization (ESI) source in

positive ion mode. A Waters ACQUITY UPLC HSS T3 column (1.8 µm, 2.1 × 100 mm)

was used for amino compound separation with a flow rate at 0.5 ml/min and column

temperature of 55 °C. The mobile phases were (A) water containing 0.05% and 0.1%

formic acid (v/v), (B) acetonitrile containing 0.05% and 0.1% formic acid (v/v). The

gradient elution was 2% B kept for 0.5 min, then changed linearly to 10% B during 1

min, continued up to 35% B in 2 min, increased to 95% B in 0.1 min and maintained for

1.4 min. Multiple Reaction Monitoring (MRM) was used to monitor all amino

compounds. The mass parameters were as follows, Curtain gas flow 35 L/min, Collision

Gas (CAD) was medium, Ion Source Gas 1 (GS 1) flow 60 l/min, Ion Source Gas 2 (GS

2) flow 60 l/min, IonSpray Voltage (IS) 5500V, temperature 600 °C. All amino compound

standards were purchased from sigma and Toronto research chemical (TRC).

UHPLC-MS quantification of Hormones

250 µl plasma was diluted with 205 µl aqueous solution, For SPE experiments, HLB

(Waters, USA) was activated with 1.0 ml of dichloromethane, acetonitrile, methanol,

respectively and was equilibrated with 1.0 ml of water. The pretreated plasma sample

was loaded onto the cartridge and was extracted using gravity. Clean up was

accomplished by washing the cartridges with 1.0 ml of 25% methanol in water. After

drying under vacuum, samples on the cartridges were eluted with 1.0 ml of

dichloromethane. The eluted extract was dried under nitrogen and the residual was

dissolved with 25% methanol in water and was transferred to an autosampler vial prior

to LC−MS/MS analysis. The analysis was performed by UHPLC coupled to an AB Sciex

Qtrap 5500 mass spectrometry (AB Sciex, US) with the atmospheric pressure chemical

ionization (APCI) source in positive ion mode. A Phenomone Kinetex C18 column (2.6

µm, 2.1 × 50 mm) was used for steroid hormone separation with a flow rate at 0.8

ml/min and column temperature of 55 °C. The mobile phases were (A) water containing

1mM Ammonium acetate, (B) Methanol containing 1mM Ammonium acetate. The

gradient elution was 25% B kept for 0.9min, then changed linearly to 40% B during

0.9min, continued up to 70% B in 2 min, increased to 95% B in 0.1 min and maintained

for 1.6 min. Multiple Reaction Monitoring (MRM) was used to monitor all steroid

hormone compounds. The mass parameters were as follows, Curtain gas flow 35 l/min,

Collision Gas (CAD) was medium, Ion Source Gas 1 (GS 1) flow 60 l/min, Ion Source

Gas 2 (GS 2) flow 60 l/min, Nebulizer Current (NC) 5, temperature 500 °C. All steroid

hormone profiling compound standards were purchased from sigma, Toronto research

chemical (TRC), Cerilliant and DR. Ehrenstorfer.

ICP-MS quantification of trace elements

200 µl of whole blood were transferred into a 15 mL polyethylene tube and diluted 1:25

with a diluent solution consisting of 0.1% (v/v) Triton X-100, 0.1% (v/v) HNO_3,2mg/L AU,

and internal standards (20 µg/L). The mixture was sonicated for 10min before ICP-MS

analysis. Multi-element determination was performed on an Agilent 7700x ICP-MS

(Agilent Technologies, Tokyo, Japan) equipped with an octupole reaction system (ORS)

collision/reaction cell technology to minimize spectral interferences. The continuous

sample introduction system consisted of an autosampler, a quartz torch with a 2.5-

mmdiameter injector with a Shield Torch system, a Scott double-pass spray chamber

and nickel cones (Agilent Technologies, Tokyo, Japan). A glass concentric MicroMist

nebuliser (Agilent Technologies, Tokyo, Japan) was used for the analysis of diluted

samples.

UPLC-MS quantification of water-soluble vitamins

200 µl plasma were deproteinized with 600 µl methanol (Merck), water, acetic acid

(9:1:0.1) containing internal standards, thiamine-(4-methyl-13C-thiazol-5-yl-13C3)

hydrochloride (Sigma-Aldrich), levomefolic acid-13C, d3, riboflavin-13C,15N2, 4-

pyridoxic acid-d3 and pantothenic acid-13C3,15N hemi calcium salt (Toronto Research

Chemicals). 500 µl supernatant were dried by nitrogen flow. 60 µl water were added to

the residues, vortexed, the mixture was centrifuged and the supernatant was for

analysis. The analysis was performed by UPLC coupled to a Waters Xevo TQ-S Triple

Quad mass spectrometry (Waters, USA) with the electrospray ionization (ESI) source in

positive ion mode. A Waters ACQUITY UPLC HSS T3 column (1.7 µm, 2.1 × 50 mm)

was used for water-soluble vitamins separation with a flow rate at 0.45 ml/min and

column temperature of 45 °C. The mobile phases were (A) 0.1 % formic acid in water,

(B) 0.1% formic acid in methanol. The following elution gradient was used: 0–1

min,99.0%–99.0% A; 1–1.5 min, 99.0% A–97.0% A; 1.5–2 min, 97.0% A–70.0% A,2–

3.5 min, 70% A–30% A; 3.5–4.0 min, 30%A–10.0%A; 4.0–4.8 min, 10%A–10.0%A; 4.9–

6.0 min, 99.0%A–99.0%A. Multiple Reaction Monitoring (MRM) was used to monitor all

water-soluble vitamins. The mass parameters were as follows, the capillary voltages of

3000V and source temperature of 150°C were adopted. The desolvation temperature

was 500°C. The collision gas flow was set at 0.10 ml/min. The cone gas and

desolvation gas flow were 150 l/h and 1000 l/h, respectively. All water-soluble vitamins

standards were purchased from Sigma-Aldrich (USA).

UPLC-MS quantification of fat-soluble vitamins

250 µl plasma were deproteinized with 1000 µl methanol and acetonitrile, (v/v,1:1)

(Fisher Chemical) containing internal standards, all-trans-Retinol-d5, 25-

HydroxyVitamin-D2-d6, 25-HydroxyVitamin-D3-d6, vitamin K1-d7, α-Tocopherol-d6

(Toronto Research Chemicals). 900 µl supernatant were dried by nitrogen flow. 80 µl

80% acetonitrile were added to the residues, vortexed, the mixture was centrifuged, and

the supernatant was used for analysis. The analysis was performed by UPLC coupled

to an AB Sciex Qtrap 4500 mass spectrometry (AB Sciex, USA) with the atmospheric

pressure chemical ionization (APCI) source in positive ion mode. A Waters ACQUITY

UPLC BEH C18 column (1.7 µm, 2.1 × 50 mm) was used for fat-soluble vitamins

separation with a flow rate at 0.50 ml/min and column temperature of 45 °C. The mobile

phases were (A) 0.1 % formic acid in water, (B) 0.1% formic acid in acetonitrile. The

following elution gradient was used: 0–0.5 min,60.0%–60.0% A; 0.5–1.5 min, 60.0% A–

20.0% A; 1.5–2.5 min, 20.0% A–0% A,2.5–4.5 min, 0% A–0% A; 4.5–4.6 min, 0%A–

60.0%A; 4.6–5.0 min, 60.0%A–60.0%A. Multiple Reaction Monitoring (MRM) was used

to monitor all fat-soluble vitamins. The mass parameters were as follows, Curtain gas

flow 30 l/min, Collision Gas (CAD) was medium, Ion Source Gas 1 (GS 1) flow 40 l/min,

Ion Source Gas 2 (GS 2) flow 50 l/min, Nebulizer Current (NC) 5, temperature 400 °C.

All fat-soluble vitamins standards were purchased from Sigma-Aldrich (USA), Toronto

research chemical (TRC).

Sequencing of the TCRβ CDR3 immune repertoire

10 ml whole blood was centrifuged at 3,000 r/min for 10 min, then 165 µl buffy coat

were obtained to extract DNA using MagPure Buffy Coat DNA Midi KF Kit (Magen,

China). The DNA was sequenced on the BGISEQ- 500 platform using 200 bp singled-

end reads. The data processing was performed using Immune IMonitor (Zhang et al.,

2015a).

Medical Parameters

All the volunteers were recruited during the physical examination. The medical test

including blood tests, urinalysis, routine examination of cervical secretion. All the

medical parameters were measured by the physical examination center and shown in

Table S1A and Table S1E.

Facial skin features

The volunteers were required to clean their face without makeup after they got up in the

morning. The volunteer's frontal face was photographed by VISIA-CRTM imaging

system (Canfield Scientific, Fairfield, NJ, USA) equipped with chin supports and

forehead clamps that fix the face during the photographing process and maintain a fixed

distance between the volunteers and the camera at all times. Eight indices were

obtained including spots, pores, wrinkles, texture, UV spots, porphyrins, brown spots

and red area from the cheek and forehead, respectively (Table S1A, S1E). The

percentile of index was calculated based on the index value ranked in the age-matched

database (Table S1A, S1E). The higher the percentile of index, the better the facial skin

appears.

Physical fitness test

8 kinds of tests were performed to evaluate volunteers' physical fitness condition (Table

S1A, S1E). Vital capacity was measured by HK6800-FH (Hengkangjiaye, China).

Single-legged stance with eyes closed was measured by HK6800-ZL. Choice reaction

time was measured by HK6800-FY. Grip strength was measured by HK6800-WL. Sit

and reach was measured by HK6800-TQ. Sit-ups was measured by HK6800-YW. Step

index was measured by HK6800-TJ. Vertical jump was measured by HK6800-ZT. We

got a measure value from each test. Then each measure value score was assigned

grades A through E based on its corresponding age-matched database.

QUANTIFICATION AND STATISTICAL ANALYSIS

Quality control, Taxonomic annotation and abundance calculation

The sequencing reads of fecal samples and saliva samples were quality-controlled and

then aligned to hg19 to remove human reads as described previously(Fang et al.,

2018). Stringent condition for removal of host sequences was used for cervical

samples(Li et al., 2018), through alignment to the GRCh38 reference.

Taxonomic assignment of the high-quality cervical metagenomic data and saliva

metagenomic data were performed using MetaPhlAn2(Segata et al., 2012).

Taxonomic assignment of the high-quality fecal metagenomic data was performed using

the reference gene catalog comprising 9,879,896 genes(Li et al., 2014). Taxonomy of

the fecal MLGs/MGSs were then determined from their constituent genes, as previously

described(Moll1 et al., 2019; Nielsen et al., 2014; Qin et al., 2012; Wang and Jia, 2016).

Random-forest on the influence of female life history factors

The factors in female life history questionnaire were fitted against the relative

abundances of metaphlan2 profile (found in at least 10% of the samples) in the cervical

samples using default parameters in the RFCV regression function from randomForest

package in R. Female life history factors are dummy variables such as pregnancy

history (yes, no) or frequency variables such as number of caesarean section (0, 1, 2),

except age is continue variables, see table S1A. In addition to comparing the predict

power across factors, we use regression model instead of classification model here.

Spearman's correlation between measured value and 5-fold cross-validation predicted

value was calculated as model performance metric, then rank the key predictable

factors. P-value was done using 999 permutation test.

The global effect size between vagino-cervical microbiome and omics data.

To evaluate the combined effect size of vagino-cervical microbiome on omics data, we

used forward stepwise redundancy analysis of omics data lists on the relative

abundances of metaphlan2 profile in forward.sel function in the packfor package in R.

This analysis provided a global versus global association between any two omics

datasets that maximize the associations by use the most predict power non-redundant

predictors.

The factors in each type of omics predicted by vagino-cervical microbiome

The factors in each type of omics were fitted against the relative abundances of

metaphlan2 profile (found in at least 10% of the samples) in the cervical samples using

default parameters in the RFCV regression function from randomForest package in R.

Omics data are mix of dummy variables and continue variables, see table S1A. In

addition to comparing the predict power across factors, we use regression model

instead of classification model here. Spearman's correlation between measured value

and 5-fold cross-validation predicted value was calculated as model performance

metric, then rank the top 8 predictable factors in each type. P-value was done using 999

permutation test,

Transformation of metagenomics profile for composition data analysis

905 Vaginal cervical relative abundance profile was composition data, so we adopt arcsin

906 sqrt-transformation to make it resemble continuous for the downstream analysis

907 (implemented in MaAsLin software, Morgan et al 2012).

Wisdom of crowds for robust network construction between vagino-cervical microbial species and other omics data

A new multi-omics analyses method (Marbach et al., 2012) was used to integrated

coefficient of linear regression, variance importance from randomForest and

Spearman's correlation to construct omics flux networks and then visualized in

CytoScape. The details are as indicated:

Step 1: Data processing. All categorical variables in other omics data were converted

into continuous variables, and nominal variables were converted into dummy variables.

Missing values were filled with median, the samples which contained more than 70%

missing variables were removed. The microbial species less than10% in all the samples

were also removed. Removed near zero variable variables. For linear models, variables

were normalized. Outliers were defined as outside of the 95% quartiles and removed.

Step 2: Method implementation. Random forest variable importance was used to

identify the most important predictor variables(Louppe et al., 2013). RFCV regression

function from randomForest package in R with default parameter was used to get the 5-

fold average variable importance. We calculated the Spearman's correlation with the

cor.test function in base R software. For linear regression, we considered penalty

regression to overcome the sparse and co-linear problem, cv.glmnet function from

glmnet package in R was first used to figure out the best lambda parameter,

bootstrapping glmnet with 0.632 re-sampling was performed 100 times, then we

obtained the best lambda.

Step 3: Construction of robust networks. We kept first 5 average ranks for each target

variable and retained edges with Spearman's correlation Q-value <0.1. Then ggplot

package in R was used to make barplot for some representative female life history

factors (Figure 6). CytoScape was also used to visualize the omics network (Figure 7).

The second cohort was analyzed using the same statistical method. Combining P-value

is computed using Edgington method from metap package in R. Benjamini and

Hochberg methods were used to adjust the multiple test P-value. The correlation is

identified based on BH-adjusted P-value <0.1 when the similar microbial distribution

pattern shown in the initial study cohort and the second cohort.

Association between microbiome pathways and other omics

Pathway profile was calculated from the vagino-cervical metagenomic data using

humann2. Spearman's correlation was calculated between the relative abundance of

each pathway and other numerical data collected. R package heatmap were used for

visualization. Q-value <0.1 was considered as significant.

DATA AND SOFTWARE AVAILABILITY
Metagenomic sequencing data for all samples have been deposited to the (CNGB)

database under the accession code CNP0000287.

1148 Healthy women

including:
the initial study cohort: 516 individuals
the second cohort: 632 individuals

Saliva microbiome

(only in the second cohort)

Fecal microbiome

Vagino-cervical microbiome

Shotgun metagenomics

39 amino acids (plasma)

13 hormones (plasma)

9 vitamins (plasma)

9 trace elements (whole blood)

622 immune indices (buffy coat)

Blood biochemistry: alkaline phosphatase,
fasting blood sugar, bilirubin, globulin, HDL,
LDL, creatinine (serum)

Metabolites

Immune indices

Medical test

BMI, chest circumference, uric acid, leucorrhea cleanliness

Physical fitness test
vital capacity
grip strength
sit and reach
sit-ups
step index
vertical jump
choice reaction time
single-legged stance with eyes closed

Facial skin feature
spots
pores
wrinkles
texture
UV spots
porphyrins
brown spots
red area

3 kinds of questionnaires

Female life history questionnaire
Lifestyle questionnaire
Psychological questionnaire

A

B

Cohort
the initial study cohort
the second cohort

Months of Breastfeeding
2 6 12 18 24 30 40 NA

k__Bacteria   k__Viruses   k__Eukaryota   k__Archaea

Gardnerella vaginalis   Lactobacillus iners   Lactobacillus crispatus   Cyclovirus NGchicken15 NGA 2009   Atopobium vaginae

Lactobacillus sp 7 1 47FAA   Bifidobacterium breve   Streptococcus agalactiae   Pepper vein yellows virus   Lactobacillus gasseri

Lactobacillus jensenii   Prevotella bivia   Streptococcus anginosus   Escherichia coli   Lactobacillus johnsonii

Lactobacillus delbrueckii   Bifidobacterium bifidum   Prevotella timonensis   Streptococcus pasteurianus   Chlamydia trachomatis

Influenza A virus   Staphylococcus aureus   Bifidobacterium dentium   Begomovirus associated DNA III   Enterobacteria phage lambda

Malvastrum leaf curl Philippines betasatellite Ureaplasma urealyticum   Torque teno virus 28   Anaerococcus lactolyticus   Ralstonia unclassified

Bifidobacterium longum   Alphapapillomavirus 14   Porphyromonas bennonis   Tomato yellow leaf curl China betasatellite Prevotella disiens

Torque teno virus   Ureaplasma unclassified   Pseudomonas stutzeri   Prevotella amnii   Pseudomonas unclassified

Mycoplasma hominis   Rothia mucilaginosa   others