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Identification of an Intestinal Microbiota Signature Associated With Severity of Irritable Bowel Syndrome



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BACKGROUND & AIMS: We have limited knowledge about the association between the composition of the intestinal microbiota and clinical features of irritable bowel syndrome (IBS). We collected information on the fecal and mucosa-associated microbiota of patients with IBS and evaluated whether these were associated with symptoms. **METHODS:** We collected fecal and mucosal samples from adult patients who met the Rome III criteria for IBS at a secondary/tertiary care outpatient clinics in Sweden, as well as from healthy subjects. The exploratory set comprised 149 subjects (110 with IBS and 39 healthy subjects); 232 fecal samples and 59 mucosal biopsy samples were collected and analyzed by 16S ribosomal RNA targeted pyrosequencing. The validation set comprised 46 subjects (29 with IBS and 17 healthy subjects); 46 fecal samples, but no mucosal samples, were collected and analyzed. For each subject, we measured exhaled H₂ and CH₄, oro-anal transit time, and the severity of psychological and gastrointestinal symptoms. Fecal methanogens were measured by quantitative polymerase chain reaction. Numerical ecology analyses and a machine learning procedure were used to analyze the data. **RESULTS:** Fecal microbiota showed covariation with mucosal adherent microbiota. By using classic approaches, we found no differences in fecal microbiota abundance or composition between patients with IBS vs healthy patients. A machine learning procedure, a computational statistical technique, allowed us to reduce the 16S ribosomal RNA data complexity into a microbial signature for severe IBS, consisting of 90 bacterial operational taxonomic units. We confirmed the robustness of the intestinal microbial signature for severe IBS in the validation set. The signature was able to discriminate between patients with severe symptoms, patients with mild/moderate symptoms, and healthy subjects. By using this intestinal microbiota signature, we found IBS symptom severity to be associated negatively with microbial richness, exhaled CH₄, presence of methanogens, and enterotypes enriched with Clostridiales or *Prevotella* species. This microbiota signature could not be explained by differences in diet or use of medications. **CONCLUSIONS:** In analyzing fecal and mucosal microbiota from patients with IBS and healthy individuals, we identified an intestinal microbiota profile that is associated with the severity of IBS symptoms. Trial registration number: NCT01252550.

Irritable bowel syndrome (IBS) is the most prevalent functional gastrointestinal disorder in Western societies. It affects approximately 11% of the adult population and strongly impairs quality of life, social function, work productivity, and brings substantial costs to health care services.¹ The etiology of IBS remains poorly understood and the search for biomarkers is ongoing.²

It is now well accepted that IBS is a disorder involving multiple pathophysiological mechanisms in which composition of gut microbiota has been proposed as one of the potentially important factors.^{3,4} Since the first study that investigated the fecal microbiota composition of IBS patients and healthy subjects using a molecular-based approach,⁵ many studies have followed using targeted approaches,⁶ specifically quantitative polymerase chain reaction (PCR).^{6,7} More recently, the use of advanced tools has allowed a better overview of gut microbiota composition,^{6,8,9} function,¹⁰ and metabolite production^{11,12} in IBS. Even though gut microbiota alterations seem to exist in IBS, no uniform gut microbiota pattern in IBS has been shown. The existing inconsistencies among currently available data in IBS may be attributed to several factors including heterogeneity of gut microbiota profiling methods, inherent individual microbiota variability, and differences in inclusion criteria, as well as sample size. This highlights the difficulty in finding robust microbiota markers associated with IBS clinical parameters.³

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Abbreviations used in this paper: AUC, area under the curve; AUROC, area under the receiver operating characteristic curve; BMI, body mass index; FODMAP, Fermentable, Oligo-, Di-, Mono-saccharides And Polyols; GI, gastrointestinal; HAD, Hospital Anxiety and Depression; IBS, irritable bowel syndrome; IBS-C, irritable bowel syndrome with constipation; IBS-D, irritable bowel syndrome with diarrhea; IBS-M, mixed irritable bowel syndrome; IBS-SSS, Irritable Bowel Syndrome Severity Scoring System; JSD, Jensen Shannon divergence; LASSO, least absolute shrinkage and selection operator; OATT, oro-anal transit time; OTU, operational taxonomic unit; PC, principal component; PCR, polymerase chain reaction; rRNA, ribosomal RNA; RV, regression vector.

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and shows the need for large and well-characterized cohorts to obtain valid and reliable analyses of the association between clinical symptoms and microbiota composition and function in IBS.

Fecal microbiota has been the target of most studies because of its convenient accessibility. However, mucosal microbiota is of great interest given its proximity to host cells because host–microbe interactions have been proposed to be of relevance for symptom generation in IBS.⁴ Although the analysis of mucosal microbiota involves more invasive sampling methods, several studies have investigated colonic mucosal samples obtained by sigmoidoscopy, either after bowel cleansing¹³ or using unprepared biopsy specimens.^{14–16} The use of unprepared biopsy samples offers the advantage to avoid perturbation of the microbiota composition.¹⁷ Large cohort studies in IBS patients combining paired microbiota samples originating from fecal and mucosa samples are rare, but a few smaller studies using next-generation sequencing exist.^{13,16}

Thus, there is currently a need for an improved understanding of gut microbiota composition in IBS patients and for the potential role played by the gut microbiota in the generation of IBS symptoms. In this study, we therefore aimed to determine the fecal and mucosa-associated microbiota, and the link to clinical symptoms in a large and well-characterized cohort of IBS patients.

Materials and Methods

Subject Recruitment and Study Design

Adult patients, aged 18–65 years and fulfilling the Rome III criteria¹⁸ for IBS, were included prospectively at a secondary/tertiary care outpatient clinic (Sahlgrenska University Hospital, Gothenburg, Sweden). The diagnosis was based on a typical clinical presentation and additional investigations if considered necessary by the gastroenterologist (H.T. or M.S.). Classification into IBS subtypes according to the Rome III criteria was performed based on Bristol Stool Form scale characteristics: IBS with constipation (IBS-C), IBS with diarrhea (IBS-D), mixed IBS (IBS-M), or untyped IBS.¹⁸ Exclusion criteria included the use of probiotics or antibiotics during the study period or within 1 month before inclusion, another diagnosis that could explain the gastrointestinal (GI) symptoms, severe psychiatric disease as the dominant clinical problem, other severe diseases, and a history of drug or alcohol abuse. A healthy control group was recruited by use of advertisement and checked by interview and a questionnaire to exclude chronic diseases and any current GI symptoms.

All participants provided written informed consent to participate after verbal and written information about the study. The Regional Ethical Review Board at the University of Gothenburg approved the study before the start of subject inclusion.

Subject Characterization

Demographic information and body mass index were obtained in all subjects. IBS patients reported their current use of medications and completed questionnaires to characterize their symptom severity and bowel habits. The IBS Severity Scoring System (IBS-SSS),¹⁹ the Hospital Anxiety and Depression (HAD) scale,²⁰ a 4-day food diary,²¹ and a 2-week stool diary based on

the Bristol stool form scale.²² IBS severity was based on validated cut-off scores on IBS-SSS (mild IBS, IBS-SSS score < 175; moderate IBS, IBS-SSS score of 175–300; and severe IBS, IBS-SSS score > 300).¹⁹

The oro-anal transit time (OATT) (radiopaque marker study)²³ and the amount of exhaled H₂ and CH₄ after an overnight fast (ie, not after intake of any substrate), also was determined in IBS patients (see [Supplementary Material](#) for more details).

Fecal and Mucosal Sample Collections and DNA Extraction

Fecal samples were collected from 195 subjects in RNAlater solution (Ambion, Courtaboeuf, France). For most of the IBS subjects, 2 fecal samples were collected (average, 26 ± 16 days between the 2 samples). A first set, referred to as the *exploratory set*, comprised 149 subjects (110 IBS and 39 healthy subjects), from whom 232 fecal samples and 59 biopsy samples were collected and analyzed. A second set, referred to as the *validation set*, comprised 46 subjects (29 IBS and 17 healthy subjects), from whom 46 fecal samples, but no biopsy samples, were collected and analyzed ([Supplementary Table 1](#)). The division into 2 study sets was based on sampling date.

Fecal DNA was extracted using mechanical lysis (Fastprep FP120; ThermoSavant, Illkirch, France) followed by phenol/chloroform-based extraction as previously described.²⁴ Biopsy specimens from the sigmoid colon were obtained from 59 subjects (39 IBS and 20 healthy subjects). The biopsy specimens were taken 25–35 cm proximal of the anus during an unprepared sigmoidoscopy. Once collected, biopsy specimens were placed immediately in liquid nitrogen and stored at -80°C until further analysis. Mucosal adherent microbiota DNA was isolated using an adapted protocol based on Godon et al²⁵ (see the [Supplementary Material](#) for more detail). Routine histopathology of biopsy specimens confirmed the absence of active inflammation.

Microbial Composition Assessment

Hypervariable 16S ribosomal RNA (rRNA) regions (V5–V6) were amplified using primers 5'-AGGATTAGATACCCTGGTA-3' and 5'-CRRACGAGCTGACGAC-3'. Sequencing was performed by DNA Vision SA (Charleroi, Belgium) on a 454 Life Sciences Genome Sequencer FLX instrument (Roche, Basel, Switzerland) using titanium chemistry. Raw reads quality filtering and trimming, operational taxonomic units (OTU) clustering, and taxonomic assignment all were performed using the LotuS v1.32 pipeline²⁶ (see the [Supplementary Material](#) for more detail).

Detection of Methanobacteriales by Quantitative PCR

Fecal extracted DNA were subjected to quantitative PCR using primers targeting the *Methanobacteriales* order Mtb857F (5'-CGWAGGGAAGCTGTTAAGT-3') and Mtb1196R (5'-TACCCTCGTCCACTCCTT-3'), as has been described previously.²⁷ PCR results then were translated as the presence or absence of dominant *Methanobacteriales* in fecal samples using 10⁶ rRNA genes copies per gram of wet fecal content as the threshold, as defined by the lowest detected value in the standard curve.

Numerical Ecology and Statistical Analysis

α -Diversity (diversity within samples) was assessed using the number of observed OTUs rarefied at the same sequencing depth (3500 sequences per sample in this study) using the vegan R package.²⁸ β -Diversity (diversity between samples) was assessed by square-root Jensen–Shannon divergence metrics,²⁹ referred to as the Jensen–Shannon distance (JSD) in this article, as well as the Bray–Curtis distance. Enterotype stratification was identified in fecal samples (1 sample per individual) using previously described methods with the Dirichlet multinomial mixture model.³⁰

A machine learning procedure to identify a microbial signature for IBS severity was implemented using L1 regularized logistic regression³¹ (least absolute shrinkage and selection operator [LASSO]) using the LIBLINEAR library³² validated through a 10-fold independent cross-validation. Features selection and data transformation was processed as previously described.³³ The performance of prediction models was assessed for its discriminative ability using the area under the receiver operating characteristic curve (AUROC) on exploratory and validation data sets. OTUs selected by machine learning were characterized further by their prevalence in healthy subjects and in patients with severe IBS (IBS-SSS > 300), and by their phylogenetic specificity (see [Supplementary Material](#) for more detail).

Co-inertia analysis was used to identify the relationship between the fecal and biopsy microbiota data sets, as well as the relationship between a microbial signature for IBS severity and the clinical data, using the ade4 R package.³⁴ The overall similarity between data sets then was measured by the regression vector (RV) coefficient.³⁴ The relationship between variables was assessed using nonparametric tests (the Wilcoxon test and Spearman correlation test) for continuous variables (eg, bacterial relative abundance, microbiota α - and β -diversity, IBS-SSS, HAD, age, body mass index [BMI], exhaled gas, and stool frequency and consistency), and the chi-squared test for categorical variables (eg, enterotypes, IBS subtypes, and

the presence or absence of methanogens). A Monte Carlo permutation test (99 permutations) was used to assess the robustness of the RV coefficient. The statistical approaches (eg, co-inertia and Monte-Carlo) applied to microbiota analysis have been thoroughly described previously.³⁵ In case of multiple testing, all *P* values were adjusted by Benjamini–Hochberg false-discovery rate correction.³⁶ All statistical analyses were performed with R software and is described in the [Supplementary Material](#).

Access to Study Data

All authors had access to the study data and reviewed and approved the final manuscript. Source codes used in this study are available from GitHub (<http://github.com/tapj/IBSMicrobiota>).

Results

Clinical Characteristics of IBS Patients and Healthy Subjects

The study cohort was divided into 2 study sets based on sampling date. The first set, the exploratory set (149 subjects: 110 IBS and 39 healthy), were recruited between April 2010 and May 2012. The second study set, the validation set (46 subjects: 29 IBS and 17 healthy), were recruited between June 2012 and November 2013. Detailed clinical and demographic characteristics for the exploratory and validation sets are summarized in [Table 1](#) and [Supplementary Figure 1](#). There were no differences between IBS patients or healthy subjects from the 2 study sets regarding sex, age, BMI, or clinical parameters after Benjamini Hochberg correction for test multiplicity. Apart from expected differences between IBS subtypes in stool characteristics and OATT, gender differences also were seen (more women in the IBS-C group,

Table 1. Clinical and Demographic Characteristics for IBS Patients and Healthy Subjects

Median (interquartile range)	Study set 1 (exploratory)		Study set 2 (validation)		Healthy set 1 vs set 2, <i>P</i> value	IBS set 1 vs set 2, <i>P</i> value
	Healthy (n = 39)	IBS (n = 110)	Healthy (n = 17)	IBS (n = 29)		
Age, y	27 (24–31)	33 (27–43)	29 (27–38)	28 (24–40)	NS	NS
Sex, male/female	13/26	41/69	6/11	5/24	NS	NS
BMI	21.9 (19.8–24.3)	22.6 (20.9–24.7)	22.4 (21.0–23.9)	22.2 (20.3–25.0)	NS	NS
Exhaled H ₂ , ppm	8.0 (0–12.0)	2.0 (0–12.3)	4.0 (1.0–8.0)	5.5 (0–21.5)	NS	NS
Exhaled CH ₄ , ppm	3.0 (1.0–6.5)	3.0 (1.0–7.5)	2.0 (1.0–2.3)	2.5 (1.0–6.3)	NS	NS
HAD anxiety	5 (2–7)	7 (5–11)	4 (2–6)	11 (7–14)	NS	NS
HAD depression	2 (1–4)	4 (2–7)	2 (1–4)	6 (3–9)	NS	NS
IBS subtype, C/D/M/U	N/A	18/43/43/2 (4 NA)	N/A	3/14/9/1 (2 NA)	N/A	NS
IBS-SSS	N/A	266 (198–359)	N/A	270 (212–347)	N/A	NS
Number of patients with severe IBS, IBS-SSS > 300	N/A	45	N/A	13	N/A	NS
Stool consistency (BSF)	4.0 (3.5–4.4)	4.0 (2.8–4.7)	3.6 (2.9–4.4)	4.5 (3.3–5.2)	NS	NS
Stool frequency (stool per day)	1.2 (1.0–1.6)	1.5 (1.0–2.1)	1.4 (1.1–2.0)	1.3 (1.1–1.6)	NS	NS
OATT, days	1.1 (0.7–1.7)	1.1 (0.6–1.8)	1.1 (1.0–1.5)	1.3 (0.9–2.1)	NS	NS

NOTE. Data are shown as median (interquartile range). Statistical significance was determined by nonparametric Wilcoxon test and Benjamini Hochberg multiplicity correction. Sex and IBS subtype balance were evaluated with the chi-squared test. NS indicates a *P* value greater than .05.

BSF, Bristol Stool Form; IBS-U, irritable bowel syndrome unsubtyped; N/A, not applicable; NA, not available.

Pearson chi-squared test, $P < .05$), but otherwise other clinical and demographic data were similar in IBS subtypes. Regarding IBS subtype distribution, no differences were observed, neither between severe and other IBS, nor between the exploratory and validation sets (Supplementary Table 2).

Fecal and Mucosal Microbiota Are Structurally Distinct but Highly Correlated

Paired mucosal and fecal microbiota samples were analyzed from 59 study subjects in the exploratory set (Supplementary Table 1). Paired comparisons of 16S rRNA gene sequencing analysis showed that fecal microbiota harbored more Firmicutes and Actinobacteria, whereas mucosal microbiota was enriched in Bacteroidetes and Proteobacteria ($P < .05$) (Figure 1A). α -Diversity of mucosal adherent microbiota, as measured by the number of OTUs, was significantly lower than that of fecal microbiota ($P < .05$) (Figure 1B). By using a co-inertia approach based on JSD metrics, mucosal microbiota was associated significantly with the fecal microbiota (RV, 0.71; $P < .001$), as shown in Figure 1C and D.

Microbiota Diversity in Fecal and Biopsy Samples

Microbiota diversity in both fecal and biopsy samples was analyzed in the exploratory set using classic ecologic descriptive approaches including α -diversity (richness as measured by number of OTUs, 97% identity) and β -diversity

(JSD and Bray-Curtis distance using bacterial genus relative abundance). Neither microbiota richness nor microbiota variability differed between groups (healthy subjects, IBS patients, IBS Rome III subtypes, or IBS severity) in the exploratory set. This was true for both fecal and biopsy samples (Supplementary Figure 2).

Enterotype Stratification in Healthy Subjects and IBS Patients

Microbiota clustering was performed on 232 fecal samples from IBS patients (including 2 samples for most patients) and healthy subjects in the exploratory set (Supplementary Table 1) using the Dirichlet multinomial mixture model.

Microbiota separated optimally into 3 distinct microbiota communities as assessed by Bayesian information criterion and the Laplace parameter (Supplementary Figure 3A and B). The 3 identified microbiota communities were similar to the previously described gut microbial enterotypes.²⁹ One enterotype was enriched in *Bacteroides* (16% of samples), 1 was enriched in *Prevotella* (14% of samples), and 1 was enriched in Clostridiales (70% of samples) (Figure 2A and Supplementary Figure 3C). Notably, distribution of enterotypes correlated with microbial richness, with *Bacteroides*-enterotyped subjects harboring the lowest richness, as compared with *Prevotella*- and Clostridiales-enterotyped subjects ($P < .05$) (Figure 2B).

Next, we analyzed enterotype distribution and association with clinical parameters. After correcting for multiple

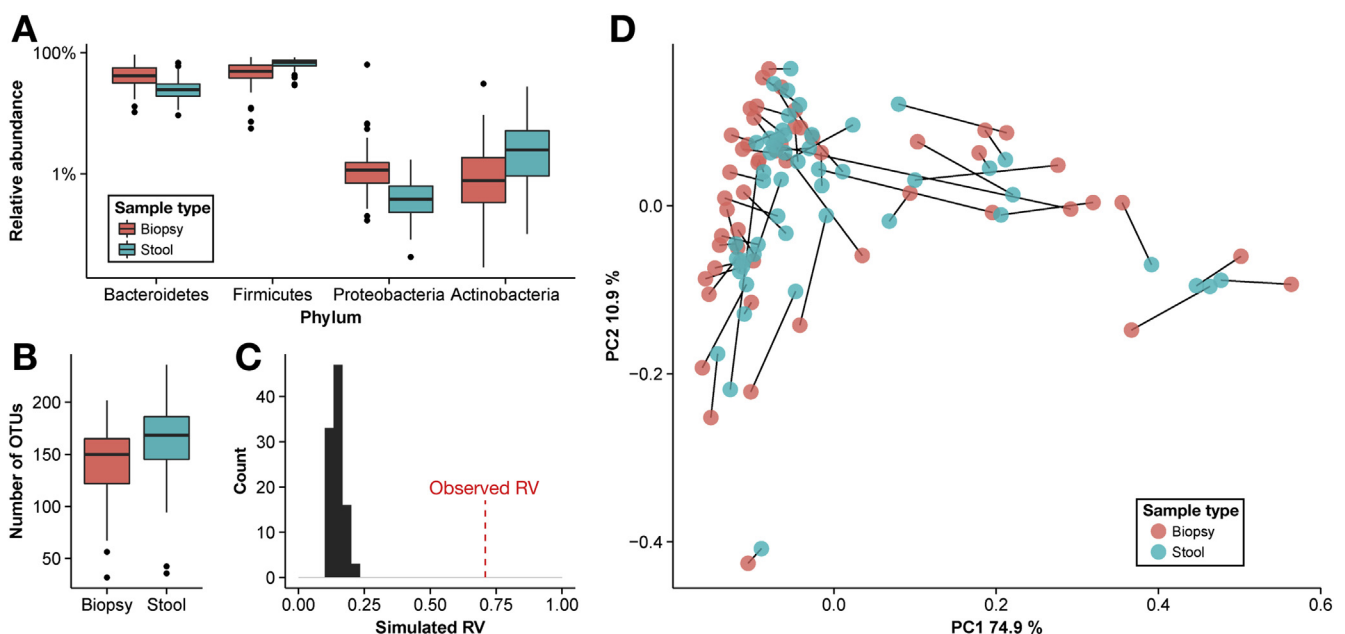


Figure 1. Taxonomic and diversity analysis of fecal and mucosal microbiota in IBS patients and healthy subjects. (A) Phylum relative abundance in stool and biopsy specimens (paired Wilcoxon test between stool and biopsy, $P < .05$). (B) The α -diversity measured by OTU number (paired Wilcoxon test, $P < .05$). (C) Similarity between fecal and mucosal microbiota measured by RV coefficient. Observed RV coefficient is illustrated by the red dashed line. The black histogram shows the distribution of RV-simulated coefficient from 99 Monte Carlo permutations (permutation test, $P < .05$; the difference between observed and simulated indicates that the observed RV was higher than what would be expected by chance, hence significant). (D) Scatter plot of paired stool-biopsy microbiota from the co-inertia analysis using JSD metrics. Biopsy and fecal sample from the same subject are linked by a black line. PCs represent the 2 first principal components from the co-inertia analysis. The length of the black line represents the distance between stool and biopsy from the same subject.

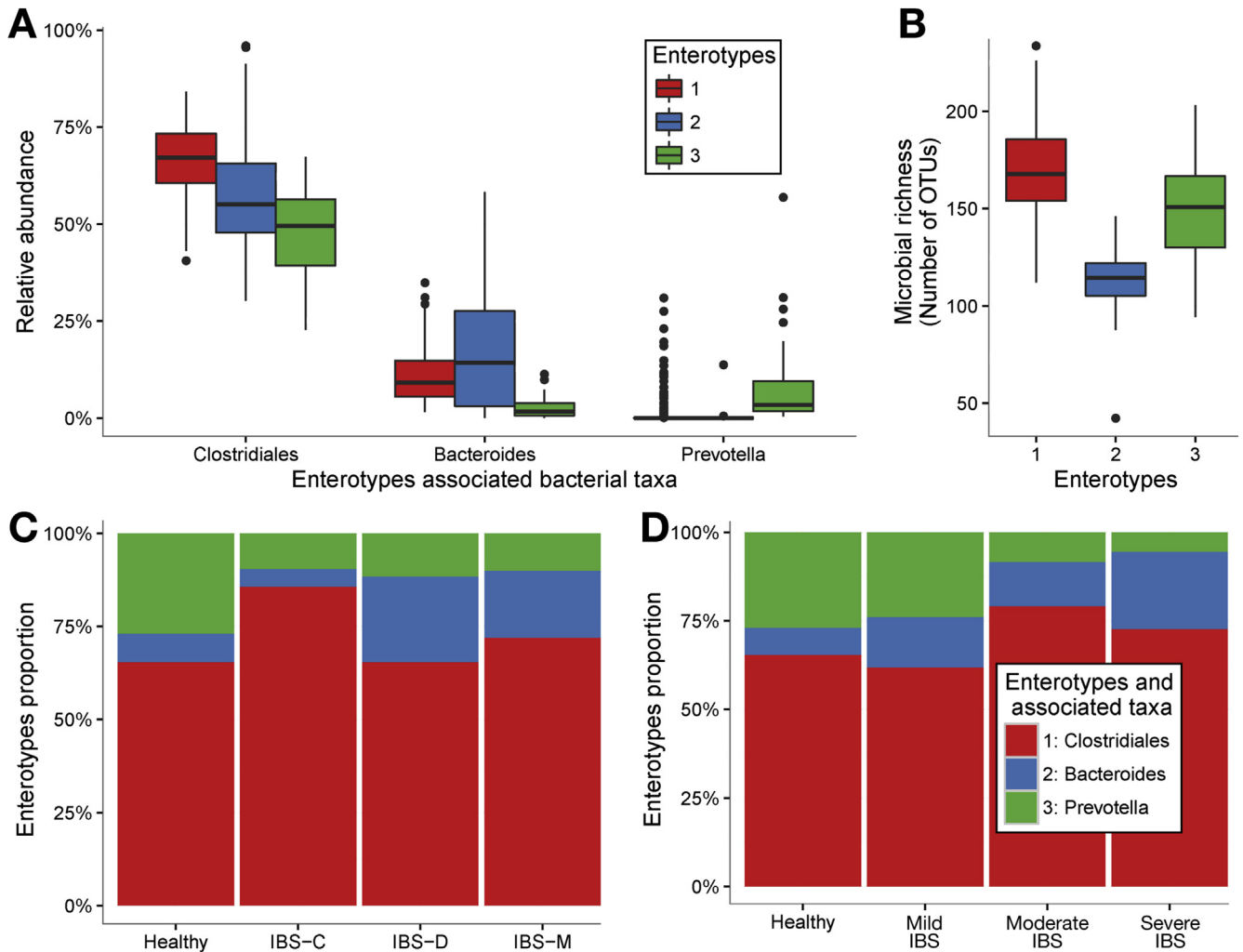


Figure 2. Enterotype richness and distribution in healthy subjects and IBS patients. (A) Abundance of the main contributors of each enterotype supports previously described enterotypes (Clostridiales, *Bacteroides*, and *Prevotella*). (B) Microbial richness of the 3 detected enterotypes: Clostridiales, *Bacteroides*, and *Prevotella* enterotypes (pairwise Wilcoxon test, $P < .05$). (C) Enterotype distribution in stool of healthy subjects and IBS subtypes (Pearson chi-squared test, $P < .05$). (D) Enterotype distribution according to severity group (Pearson chi-squared test, $P < .05$).

comparisons, no significant association was observed between enterotypes and clinical parameters including age, BMI, HAD anxiety, HAD depression, exhaled H_2 and CH_4 , or bowel habits (stool consistency and frequency) (Supplementary Figure 4A). However, enterotype distribution was associated with OATT in both healthy subjects and IBS patients (Supplementary Figure 4A). Subjects with the Clostridiales enterotype showed longer transit times than subjects with *Prevotella* and *Bacteroides* enterotypes ($P < .05$). Furthermore, the *Prevotella* enterotype was significantly more prevalent in men ($P < .05$) (Supplementary Figure 4B). Enterotype distribution differed between healthy subjects and IBS patients, with the enterotype *Bacteroides* being more frequent in IBS subjects and the *Prevotella* enterotype was more common in healthy subjects (Supplementary Figure 4C) ($P < .05$). Enterotype distribution also was associated with bowel habits (Pearson chi-squared test, $P < .05$). IBS-D and IBS-M patients had a higher prevalence of *Bacteroides* enterotype compared with IBS-C patients and healthy

subjects (Figure 2C). Regarding IBS symptom severity (IBS-SSS), the prevalence of the *Prevotella* enterotype gradually decreased as symptom severity increased ($P < .05$) (Figure 2D).

Prevalence of Methanogens in Healthy Subjects and IBS Patients

In the exploratory set, microbiota enterotyping was complemented by the detection of fecal methanogens by quantitative PCR, with specific emphasis on Methanobacteriales, which was detected in 33% of fecal samples, with a similar prevalence in healthy subjects and IBS patients (Supplementary Figure 5). A significant association was observed between exhaled CH_4 and the presence of fecal methanogens ($P < .05$) (Supplementary Figure 5A). Detection of methanogens was dependent on enterotypes because 90% of individuals who harbored Methanobacteriales belonged to the Clostridiales-enriched enterotype and

less than 5% of *Bacteroides*-enriched enterotypes had detectable level of Methanobacteriales (Supplementary Figure 5B).

The presence of methanogens was associated with IBS subtype distribution ($P < .05$). The proportion of IBS-D patients with undetectable Methanobacteriales was higher (~40%) than in IBS-C patients (~10%) (Supplementary Figure 5C). The IBS-SSS was not associated with the presence of Methanobacteriales ($P > .05$) (Supplementary Figure 5D). IBS-D patients exhaled less CH₄ than IBS-M patients (Supplementary Figure 5E), and healthy subjects exhaled less CH₄ than IBS patients with mild symptoms (Supplementary Figure 5F).

Identification of a Microbial Signature for IBS Symptom Severity

We further explored the association between IBS symptom severity and fecal microbiota composition. Compared with mild and moderate IBS subjects, a significantly higher number of OTUs ($n = 100$) could discriminate IBS subjects with severe symptoms from healthy subjects (Figure 3A). By using the bootstrapping method, we observed that the analysis was sensitive to randomness. When comparing 2 batches of 30 individuals randomly selected from the exploratory set, up to 50 bacterial OTUs could differ between the 2 batches driven by chance. In other words, compared with the total number of differential OTUs, half of the significant observations between tested groups could be detected by chance (Figure 3A). To overcome the issues related to randomness, we explored fecal microbiota in association with IBS symptom severity using an additional and more robust statistical approach, based on machine learning (LASSO). This allowed us to decrease the OTU complexity by combining them into a consensus microbial signature from an ensemble of classifiers that

discriminated patients with severe IBS from patients with moderate or mild IBS and healthy subjects. Based on IBS symptom severity, 90 of 2911 total OTUs were selected by the machine learning procedure. The predictive power of this signature was quantified by AUROC analyses. Cross-validation of the microbial signature for IBS severity obtained with the exploratory set was performed against the fecal samples validation set (area under the curve [AUC], 0.74). The signature based on fecal samples in the exploratory set also was efficient to classify mucosal samples according to IBS severity (AUC, 0.82) (Figure 3B). Next, we assessed the OTU microbial signature for IBS severity obtained from the exploratory set in the validation set ($n = 46$ individuals), which included 13 severe IBS patients (Figure 3B). In the validation set, an AUC of 0.64 was obtained, suggesting that the OTUs identified as a microbial signature for IBS severity were robust.

Taxonomic Characterization of the Gut Microbial Signature for IBS Severity

To further characterize the gut microbial signature for IBS severity, we analyzed the taxonomy of the 90 OTUs selected by the machine learning procedure (Figure 4). To assess the phylogenetic distribution of the microbial signature for IBS severity, we performed a principal coordinate analysis of the OTUs originating from the whole fecal microbiota data set ($n = 2911$ OTUs), using nucleotide identity between their respective representative sequences (Figure 4A). Notably, there were no phylogenetic lineage specific for the microbial signature for IBS severity, but instead an overlapping taxonomy between the microbial signature for IBS severity and the whole microbiota data set, suggesting that those 90 OTUs associated with IBS severity are as diverse taxonomically as the OTUs from the whole microbiota data set. When examining only the OTUs

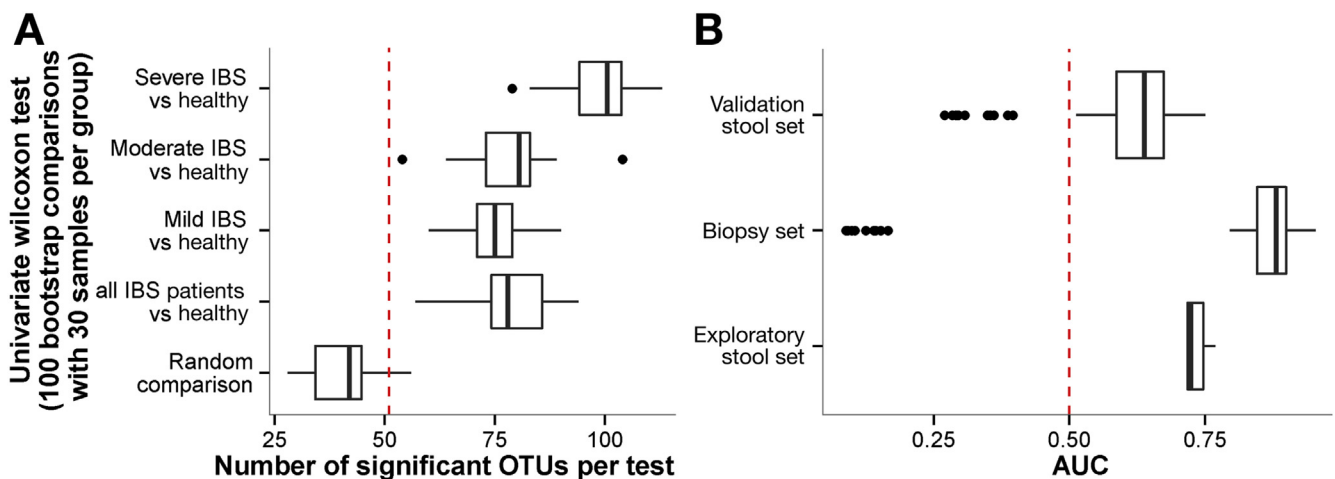


Figure 3. (A) Univariate comparison and (B) machine learning based on IBS severity. (A) For each group, 30 samples per group (mild, moderate, and severe IBS, and healthy controls, respectively) were taken randomly and each OTU was tested using a Wilcoxon test. This procedure was repeated 1000 times. The number of significant OTUs for each comparison is reported with *boxplot*. Dashed red line illustrates the random expectation defined as the 95th percentile of random comparison. (B) AUC of 1000 classification models based on 10-fold cross validation and bootstrapped 100 times. The AUC is reported for the exploratory set (50.4% sensitivity at the 80% specificity level), mucosal sample (82.9% sensitivity with 80% specificity), and validation set (39.4% sensitivity with 80% specificity). Dashed red line illustrates the random expectation defined as AUC of 0.50.

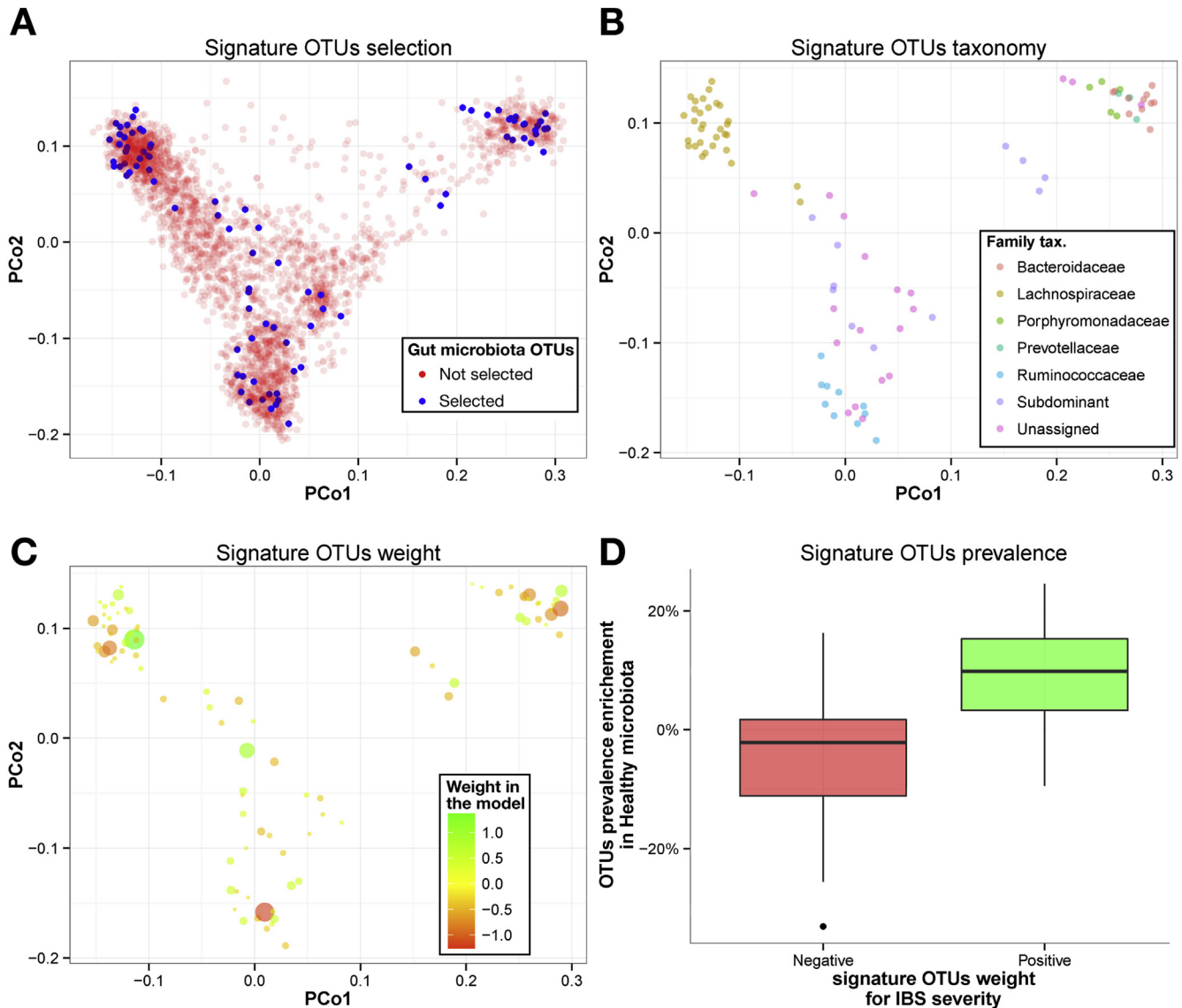


Figure 4. Taxonomic assessment of OTU microbiota signature for IBS symptom severity. Axis represent the 2 first components from principal coordinate (PCo) analysis based on the phylogenetic distance between OTU representative sequences. (A) 90 OTUs (blue dots) are selected of 2911 OTUs (red dots) by the machine learning procedure. (B) OTU microbiota signature for IBS severity colored by taxonomic assignment at family level. (C) OTU microbiota signature for IBS severity colored and sized by their weight and absolute weight in the model, respectively (green corresponding to a positive association to health and red corresponding to a positive association to IBS severity). (D) OTU prevalence enrichment in microbiota from healthy subjects as a function of their weight in the model (Wilcoxon test, $P < .05$). Green boxplot represents positive weight and red boxplot represents negative weight.

extracted from the microbial signature for IBS severity, the dominant families of the gut microbiota were represented (ie, Lachnospiraceae, Ruminococcaceae, Bacteroidaceae), but a large proportion (>25%) was not assigned at the family level (Figure 4B). Then, the 90 IBS severity discriminating OTUs were ranked according to their average weight in the model (Supplementary Table 3). In this model, OTUs with a negative weight had a positive association with IBS severity. The proportion of OTUs that showed positive or negative weight in the model was similar within Firmicutes and Bacteroidetes phyla (Figure 4C). The number of genus-unassigned OTUs from the Firmicutes (notably in the Ruminococcaceae family)

increased when they were associated with IBS severity (Pearson chi-squared test, $P < .05$). In the Firmicutes phylum, including known and dominant genera such as *Faecalibacterium*, *Oscillibacter*, *Blautia*, and *Coprococcus*, OTUs were associated positively with IBS of moderate severity or healthy status. Finally, we compared the prevalence of the 90 OTUs from the signature for IBS severity between healthy subjects and patients with severe IBS. The prevalence of OTUs that were associated positively to healthy status (ie, positive weight in the model signature) was significantly higher in the microbiota of healthy subjects compared with severe IBS patients (Wilcoxon test, $P < .05$) (Figure 4D).

Gut Microbial Signature for IBS Severity and Association With Clinical and Microbial Parameters

To evaluate the robustness of the microbial signature for IBS severity in relationship to other clinical parameters, we investigated the relative abundance of OTUs along with clinical data in a co-inertia analysis as shown in Figure 5. Clinical parameters included age, BMI, HAD anxiety, HAD depression, exhaled CH₄ and H₂, IBS subtypes, stool consistency (Bristol Stool Form) and frequency, and OATT. The first 2 co-inertia components explained more than 50% of co-variation between the IBS severity signature microbial OTUs and clinical parameters.

The IBS-SSS was confirmed to be the most important factor contributing to variation in the full data set along the first co-inertia component (PC1) (Figure 5A). In addition, OTUs that had a positive weight in the microbial signature were more prevalent in microbiota of healthy subjects and were associated positively with PC1 (Figure 5B). This suggests that OTUs selected by the machine learning procedure allowed ranking patients along the IBS severity scale (Figure 5C).

As expected, anxiety and depression were associated positively with IBS severity and this association was reflected on the gut microbial signature (Spearman rho correlation with PC1 of -0.4 and -0.32, respectively, $P < .05$) (Supplementary Table 4). In addition, exhaled CH₄ concentration (Figure 5A and D) was associated with both components PC1 ($\rho = 0.36$; $P < .05$) and PC2 ($\rho = 0.44$; $P < .05$). IBS-C and exhaled CH₄ concentrations were the most important factors explaining the variation along the second co-inertia component PC2 (Figure 5A and E). This suggests that exhaled CH₄ was associated primarily with slower transit and secondly with less severe symptoms. PC2 was to a lesser extent associated with OATT ($\rho = 0.54$; $P < .05$) and stool consistency ($\rho = -0.36$; $P < .05$). This suggests that the machine learning procedure, which originally was set up to discriminate severe IBS from mild, moderate IBS and healthy subjects, selected additional OTUs to identify IBS-C patients with high concentrations of exhaled CH₄. However, the microbial signature for IBS severity was poorly explained by age, BMI, and H₂ concentrations as shown in Figure 5A.

We then tested a posteriori these 2 first co-inertia components against microbiota parameters. These included microbial richness, absence or presence of Methanobacteriales, and enterotype stratification (Figure 5C, D, and F, respectively), which altogether were associated significantly with the first component PC1 (Wilcoxon test, $P < .05$). When plotting IBS-SSS and microbial richness, the gut microbial signature for IBS severity was linked with lower microbial richness (Figure 5C), lower levels of exhaled CH₄ (Figure 5D), and *Bacteroides*-enriched enterotype (Figure 5F). This suggests that selected OTUs from the machine learning procedure discriminated patients along a symptom severity gradient together with enterotype stratification.

Gut Microbial Signature for IBS Severity and Association With Diet and Use of Medications

A total of 111 individuals (89 IBS and 22 healthy) followed a 4-day food diary to assess nutrient intake. Average

daily intakes were calculated for energy, proportion of fat, carbohydrates, fiber, protein, and total intake of FODMAPs (Supplementary Table 5). By using a co-inertia analysis followed by a Monte Carlo test (see Supplementary Material), the overall association between dietary data and the gut microbial signature for IBS severity was tested, and no significant association could be detected (RV, 0.10; $P > .05$), indicating that the microbial signature for IBS severity is independent of overall nutrient intake, as well as intake of FODMAPs. Similar analyses regarding the influence of medications (Supplementary Table 6), including laxatives or bulking agents, acid suppressants (mainly proton pump inhibitors), antidiarrheals, and antidepressants drugs, did not show any significant associations with the microbial signature for IBS severity.

Discussion

In this study we characterized both fecal and mucosal microbiota in a large cohort of IBS patients and healthy subjects. By using a machine learning approach, we show that IBS symptom severity is associated with a distinct fecal microbiota signature that also is detected in the intestinal mucosa. This signature also is associated with microbial richness, exhaled CH₄, presence of Methanobacteriales, and enterotype stratification (assessed by using the Dirichlet multinomial mixture model), as well as stool consistency and transit time. Lower microbial richness and exhaled CH₄, as well as a reduced prevalence of Methanobacteriales and *Prevotella* enterotype, were observed in subjects with severe IBS. Interestingly, the prevalence of *Prevotella* enterotype decreased as the severity of symptoms increased, in parallel to the increased prevalence of *Bacteroides* enterotype. A graphic summary of the main findings is shown in Figure 6.

We explored the data using a combination of approaches that are well described for microbiota analysis (ie, univariate and multivariate analyses). However, when using these classic ecologic approaches, no clear differences were observed between healthy subjects and IBS patients, or between IBS subtypes as defined by the Rome III criteria. No differences were detected in fecal microbiota between IBS and healthy subjects regarding α -diversity (microbial richness), or β -diversity (pairwise JSD distance comparisons) at any taxonomy level (from phyla to species). Similar findings were observed for mucosal microbiota. A trend toward a reduction in the richness of fecal microbiota was observed in IBS subjects. Rajilić-Stojanović et al⁸ did not report a change in α -diversity, but an almost 2-fold increase of the ratio of major bacterial phyla Firmicutes:Bacteroidetes in 62 IBS patients (Rome II criteria) compared with 46 healthy subjects. In a previous study from our group, although no overall differences in microbiota composition between 37 IBS (Rome II criteria) patients and 20 healthy subjects were observed, nevertheless 2 specific IBS subclusters with altered fecal microbiota composition were identified. Interestingly, the 2 IBS subclusters accounted for 60% of IBS patients in the study, and harbored an increased Firmicutes:Bacteroidetes ratio compared with that of healthy subjects and other IBS

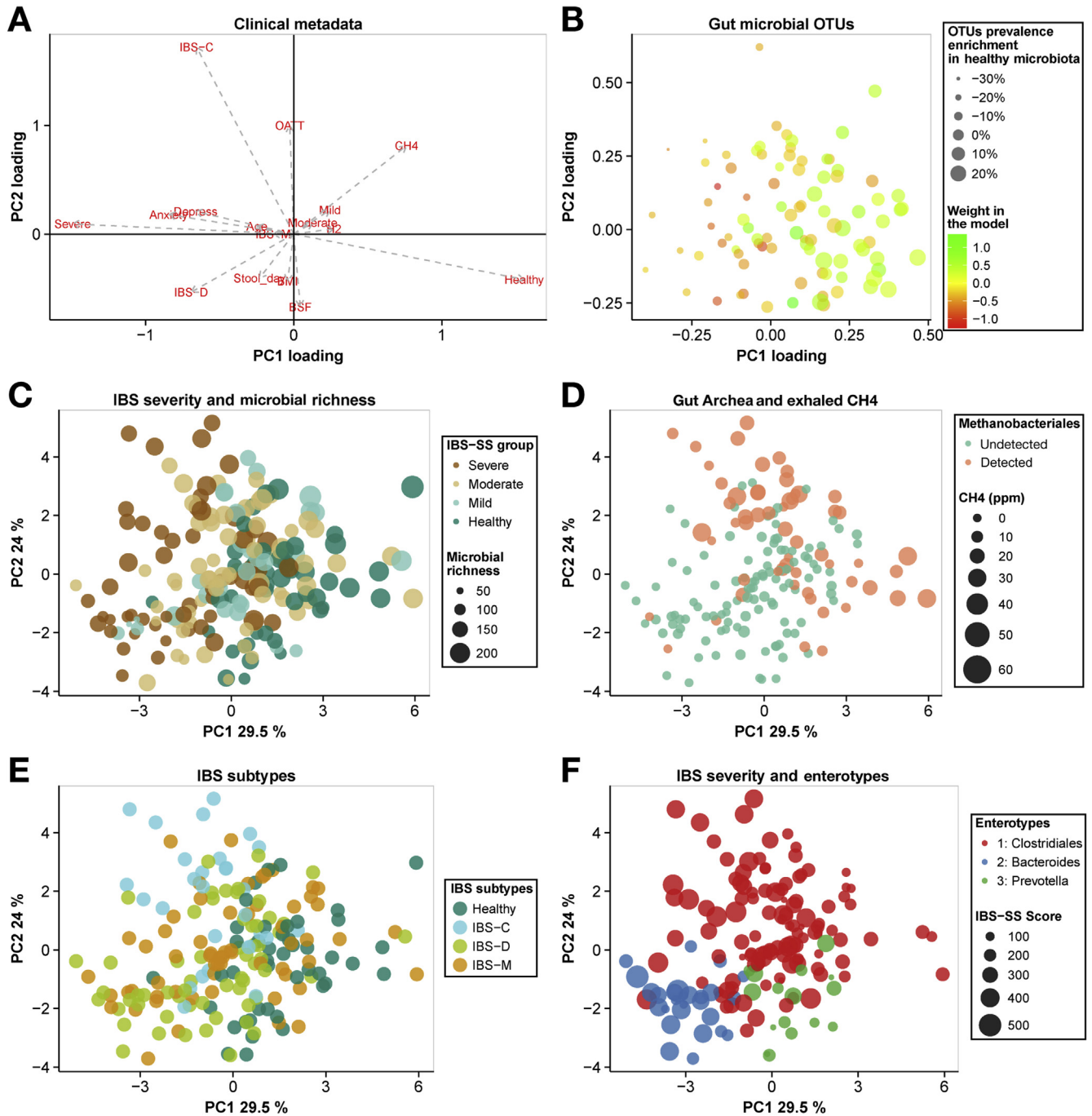


Figure 5. Clinical and microbial ecology parameter interactions with microbial signature for IBS severity. A co-inertia analysis was performed between microbial signature OTU relative abundance for IBS severity and clinical parameters. (A) Scatter plot of 2 first clinical data PC loadings. Each clinical parameter is labeled in red. (B) Scatter plot of 2 first PC loadings for microbial signature OTU relative abundance. Color accounts for weight in the model for IBS severity. Negative weights indicate OTUs associated with severe IBS. Size accounts for OTU prevalence enrichment in healthy microbiota compared with severe IBS microbiota. Positive enrichment means that an OTU was found more frequently in healthy subjects than in severe IBS patients. (C–F) Scatter plot of 2 first components of co-inertia analysis. Each dot represents a fecal microbiota sample. (C) Size accounts for microbial richness and colors for the IBS symptom severity group. (D) Size accounts for exhaled CH₄ and color for Methanobacteriales presence. (E) Color accounts for IBS subtypes. (F) Each dot represents IBS fecal microbiota sized with IBS-SSS and colored by enterotypes.

patients.⁹ Other studies, similar to ours, however, did not report significant differences between IBS and healthy subjects in either fecal or small intestinal microbiota, or reported conflicting results.^{15,37} Recently, a larger cohort from Pozuelo et al³⁸ similar to our study, reported in contrary a trend

toward a higher abundance of Bacteroidetes in 113 IBS (Rome III criteria) compared with 66 healthy subjects, as well as a lower richness in IBS subjects, probably driven by the high proportion of IBS-D subjects in that cohort. These discrepancies could be owing to several factors including

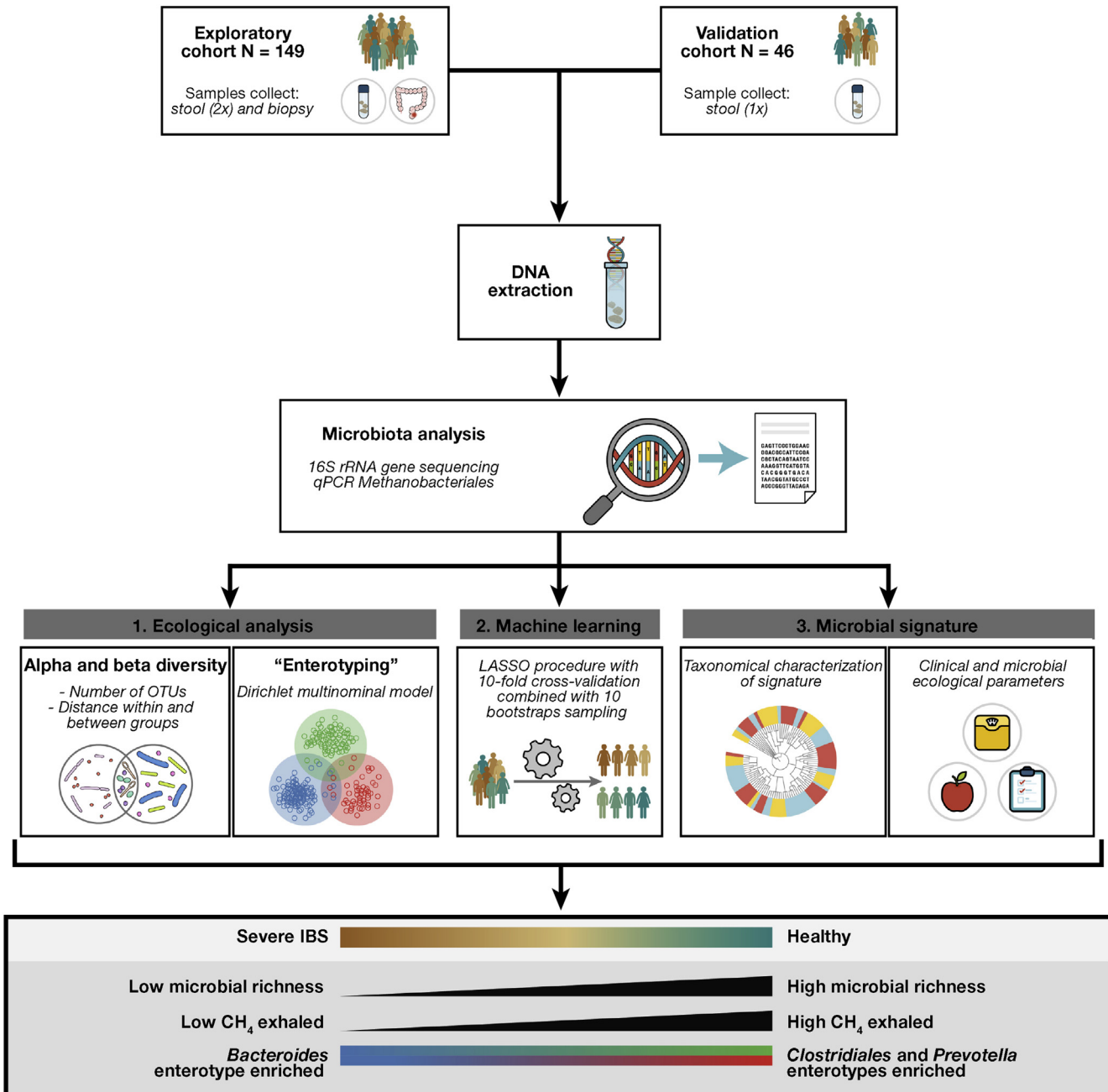


Figure 6. Graphic summary of the methods and results of the study. An exploratory ($n = 149$) and a validation set ($n = 46$) of IBS patients and healthy subjects were included in the study. DNA was extracted from fecal and sigmoid biopsy samples to assess gut microbiota by 16S rRNA gene sequencing. Methanobacteriales were detected by quantitative PCR in fecal samples. Most of the IBS patients from the exploratory set were sampled twice. Subsequent analyses of 16S sequencing data included various approaches. First, ecologic analysis included α - and β -diversity assessment and enterotype detection. Second, the machine learning procedure was used to select gut microbiota OTUs and to train models based on IBS severity on the exploratory set. The resulting microbial signature allowed classifying mucosal samples of the exploratory set, and the stool samples of the validation set, based on IBS severity. Third, the microbial signature for IBS severity was taxonomically characterized and evaluated against clinical parameters. The microbial signature for IBS severity was associated with low microbial richness, low CH₄ exhaled, *Bacteroides* enterotypes enriched, and absence of Methanobacteriales.

heterogeneity of IBS cohorts (ie, proportion of IBS subtypes, with a majority of 1 subtype, and differences in symptom severity), as well as the use of different methods (machine learning vs descriptive statistics) and 16S rRNA gene variable regions used to analyze microbiota (Supplementary Table 7 and references within), and also an absence of validation

cohorts. However, differences between IBS patients and healthy subjects were observed in our study based on enterotype distribution, with healthy subjects being more likely to belong to the *Prevotella* enterotype than IBS patients, with a concomitant increase in the prevalence of the *Bacteroides* enterotype in IBS.

We also explored paired mucosal and fecal microbiota data. The distinction between fecal and mucosal colonic microbiota in terms of composition already was detectable at the phylum level, with increased proportions of Bacteroidetes and Proteobacteria in biopsy specimens, and a higher abundance of Firmicutes and Actinobacteria were observed in fecal samples. Our data also are supported in part by Rangel et al,¹⁶ who observed different microbiota composition between mucosal and fecal samples in both healthy subjects and IBS patients, although the microbial diversity in biopsy specimens and fecal samples from their study was lower among IBS patients. In our study, the difference in microbiota composition between fecal samples and biopsy specimens was accompanied by lower richness in biopsy specimens as compared with fecal samples in both healthy subjects and IBS patients, which is consistent with previous reports.^{39,40} Although microbiota from paired mucosal and fecal samples were structurally distinct and with different α -diversity, their respective microbial β -diversity co-varied, which is consistent with the data obtained from the rhesus macaque microbiota.⁴¹ A larger number of biopsy samples would be needed to decipher whether mucosal microbiota is associated more strongly with IBS severity than fecal microbiota.

In this study, we complemented the microbiota composition analysis by quantification of microbial groups able to produce CH₄,⁴² so-called methanogens, which prevent H₂ accumulation in the gut. Production of CH₄ using H₂ is restricted to Archaea, with the order Methanobacteriales containing *Methanobrevibacter smithii* and *Methanosphaera stadtmanae* as the dominant methanogens in human beings.^{42,43} Evidence has emerged suggesting that CH₄ is linked to constipation,⁴⁴ and it has been reported that *M. smithii* is found more commonly in patients with IBS-C.⁴⁵ In our study, 33% of study subjects harbored detectable levels of Methanobacteriales, with no difference between healthy subjects and IBS patients. Interestingly, there was a significant correlation between exhaled CH₄ and the detection of *Methanobacteriales* by quantitative PCR, which is in line with previous findings.⁴⁵ In our study, the presence of Methanobacteriales differed according to IBS subtypes. IBS-D patients had more undetectable Methanobacteriales compared with the other IBS subtypes. Moreover, Methanobacteriales detection was associated positively with microbial richness in the enterotype Clostridiales in our study, which is in accordance with the study by Vandeputte et al.⁴⁶ This enterotype also was associated with longer transit time, which is consistent with another recent study.⁴⁷

We explored the data using a robust statistical analysis based on a machine learning algorithm because large microbial data sets generated from sequencing technologies might generate overfitting and overestimation.⁴⁸ Recently, there has been a growing interest in the use of machine learning techniques to detect microbiota signature in health and diseases.^{33,49} In our study, the LASSO procedure identified 90 bacterial OTUs that could be used as a composite gut microbial signature for IBS severity. The signature was robust and it still remained valid after cross-validation and testing in the validation cohort. The microbial signature was

enriched in taxonomically diverse phylotypes. At the family level, a similar proportion of OTUs within Lachnospiraceae and Ruminococcaceae were associated with health or IBS severity. OTUs known to be associated with health were more prevalent in healthy subjects than in severe IBS patients. These OTUs include *Faecalibacterium*, *Oscillibacter*, *Blautia*, and *Coprococcus* species, which previously were reported to belong to the healthy microbiota phylogenetic core.^{50,51} The phylogenetic core may represent co-evolved species within the gut microbiome that support essential gut microbial functions.⁵¹ Finally, the microbial signature for IBS severity was tested against clinical and microbial parameters. IBS severity thus was confirmed to be the strongest factor associated with the microbial signature along with the presence of methanogens, exhaled CH₄, enterotype, and microbial richness. Overall, clinical parameters other than IBS severity were not associated strongly with the microbial signature. Because recent studies reported transit time as a strong confounding factor for microbiota composition,^{46,47} it seems important to stress that OATT and IBS subtypes were not confounding factors for the microbial signature for IBS severity.

A limitation of the present study that could prevent extrapolation of the results to the general IBS population was that all patients were included at a secondary/tertiary referral center. It is well known that IBS patients seen in referral centers have more severe GI and psychological symptoms, as well as a reduced quality of life, and therefore do not reflect the general IBS population. Because it is well recognized that diet and intake of medications are 2 factors that shape gut microbiota,^{47,52} we further examined whether the microbial signature for IBS severity was influenced by these 2 factors. Our analysis on global intake of nutrients (protein, carbohydrates, fat, and calorie intake), and intake of FODMAPs did not support a relationship between these food categories and our gut microbiota signature for IBS severity. Regarding the intake of medications, although patients with severe IBS, as expected, were more likely to be treated with antidepressants than patients with milder forms of IBS, the gut microbiota signature for IBS severity was neither associated significantly with intake of antidepressants, nor with intake of other groups of medications.

To conclude, by using a large cohort and classic ecologic approaches, we could not observe differences between healthy subjects and IBS patients. However, the machine learning approach allowed identification of a gut microbial signature for IBS severity, which also could be reproduced in a validation cohort. Importantly, because of its relatively low sensitivity, this microbiota signature cannot be used as a clinical predictor of IBS severity, but as a way to explore relevant features (ie, OTUs), which deserve to be explored in future IBS microbiota studies.

Our study highlights the heterogeneity of IBS patients, and the difficulty in stratifying patients based on a microbiota profile when using only classic ecologic approaches. The use of machine learning has allowed us to circumvent the issues related to large microbial data sets and to better explore the microbial data. We were able to identify several interesting links between gut microbiota and the clinical profile.

Supplementary Material

Note: To access the supplementary material accompanying this article, visit the online version of *Gastroenterology* at www.gastrojournal.org, and at <http://dx.doi.org/10.1053/j.gastro.2016.09.049>.

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Conflicts of interest

These authors disclose the following: Boris Le Nevé, Muriel Derrien, Rémi Brazeilles, Stéphanie Cools-Portier, and Julien Tap are employees of Danone Research; Muriel Simrén has received unrestricted research grants from Danone and AstraZeneca, and has served as a consultant/advisory board member for AstraZeneca, Danone, Novartis, Almirall, Albiro, Shire, Nestlé, Glycom, and Chr Hansen, and has served on the speaker's bureau for Takeda, Tillotts, Shire, Almirall, Menarini, and Danone; Lena Öhman has received financial support for research from Danone Research, has served as a consultant for Genetic Analyses, and has received lecture fees from AbbVie and Takeda; Joël Doré has received financial support for research from Danone Research, Pfizer, and PiLeJe, and has served as a consultant/advisory board member for Danone Research, AlphaWasserman, Enterome Bioscience, and MaaT Pharma; and Hans Törnblom has served as a consultant/advisory board member for Almirall, Allergan, Danone, and Shire, and has been on the speakers' bureau for Tillotts, Takeda, Shire, and Almirall. The remaining author discloses no conflicts.

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Supplementary Materials and Methods

Questionnaires

Patients with IBS who were enrolled in the study completed questionnaires to characterize their symptom severity and bowel habits. The IBS-SSS was used to assess the severity of IBS symptoms.¹ This is a well-validated questionnaire that is based on 5 items: intensity and frequency of abdominal pain, severity of abdominal distension, bowel habits dissatisfaction, and interference with daily life. The maximum score is 500 and patients can be categorized as having mild (<175), moderate (175–300), or severe (>300) IBS symptoms. General anxiety and depression were evaluated by the HAD scale.² This is a 14-item questionnaire used to measure the severity of anxiety and depression on 2 subscales with 7 items each. Each item is scored between 0 and 3, with higher scores indicating more severe symptoms and with a total score range per subscale of 0–21.

The patients reported all bowel movements in a daily diary for 2 weeks, based on the Bristol Stool Form scale.³ The stool consistency was scored on a 7-point scale: type 1 (separate hard lumps similar to nuts, difficult to pass), type 2 (sausage shaped but lumpy), type 3 (similar to a sausage but with cracks on the surface), type 4 (similar to a sausage or snake, smooth and soft), type 5 (soft blobs with clear-cut edges), type 6 (fluffy pieces with ragged edges, a mushy stool), and type 7 (watery, no solid pieces, entirely liquid). Based on this information, the stool frequency (average number of stools/day) and stool consistency (average stool consistency/day) could be calculated. A total of 111 subjects (89 IBS and 22 healthy) completed a food diary for 4 days (3 weekdays and 1 day during the weekend). The diary included details regarding cooking methods, ingredients, brands of foods (if appropriate), time points for meals, and quantity consumed in grams or household measurements. Patients were given written instructions to enable accurate completion of the food record. The subjects were instructed to consume their usual diet. Different food items and beverages were entered in DIETIST XP version 3.1 (Kostdata.se, Stockholm, Sweden), which converts food items into nutrients and energy amounts. Composite foods (eg, casseroles) were split into ingredients (food items). DIETIST XP software covers approximately 1600 foods and 52 nutrients. DIETIST XP is designed to estimate macronutrients and micronutrients and energy intake. From the food records, average daily intakes were calculated for energy, proportion of fat, carbohydrates, protein, and FODMAPs. All nutrients in the software DIETIST XP are based on food composition data from the National Food Administration in Sweden, except for the FODMAPs, which were calculated using a new Swedish database for content of lactose, fructose, galactooligosaccharides, fructans, and polyols in foods used in Swedish diets (Liljebo et al, unpublished data).

Oro-Anal Transit Time Measurement

For the OATT measurement, the participants ingested 10 radiopaque rings every morning for 5 days. On day 6,

they ingested 5 radiopaque rings at 8:00 AM and 5 radiopaque rings at 8:00 PM to better define participants with accelerated transit. On the morning of day 7 the radiopaque rings still present in the bowel were counted at arrival at the laboratory, using fluoroscopy (Exposcop 7000 Compact; Ziehm GmbH, Nuremberg, Germany). OATT expressed in days was calculated by dividing the number of retained radiopaque rings by the daily dose (ie, 10).⁴ All medications with known effects on the GI tract (proton pump inhibitors, laxatives, antidiarrheals, opioid analgesics, prokinetics, spasmolytics, antidepressants) were discontinued at least 48 hours before intake of the first radiopaque rings.

Breath CH₄ and H₂ Measurements

This test was performed after an overnight fast (ie, not after intake of any substrate), and after the subjects had received thorough instructions to avoid a diet rich in fiber and poorly absorbed carbohydrates the day before the test. The amount of exhaled H₂ and CH₄ was measured in parts per million in end-expiratory breath samples collected in a system used for the sampling and storing of alveolar air (GaSampler System; QuinTron Instrument Company, Milwaukee, WI) and analyzed immediately using a gas chromatograph (QuinTron Breath Tracker; QuinTron Instrument Company).

Collected Data and Missing Values

A total of 196 subjects were included in this study. Information about sex, age, and BMI were available for all 196 subjects, exhaled H₂ and CH₄ in the fasting state and HAD in 185 subjects, Bristol stool form data in 166 subjects, and OATT in 181 subjects. IBS severity and subtypes were available in 133 of 139 IBS patients. Methanogen qPCR detection was performed on 231 of 278 fecal samples.

Microbial DNA Extraction From Biopsy Specimens

Once collected, biopsy specimens were placed immediately in liquid nitrogen and stored at -80°C until further analysis. Mucosal adherent microbiota DNA was isolated using the adapted protocol from Godon et al⁵ for low biomass samples.

Each biopsy sample was transferred to a tube containing 250 μ L guanidine thiocyanate, 40 μ L N-lauroyl sarcosine 10%, and 500 μ L N-lauroyl sarcosine 5%, and vortexed before incubation at 70°C for 1 hour. A total of 200 mg of glass beads (0.001 mm) were added, and each tube was mixed for 10 minutes with the Vibrobroyeur (Retsch 25/s; Newtown, PA). Fifteen milligrams of polyvinylpyrrolidone was added to the tubes that were centrifuged for 5 minutes (12,700 rpm; 4°C). The resulting supernatant then was transferred to a 2-mL sterile tube. The pellet was washed with 500 μ L of 50 mmol/L Tris pH 8, 20 mmol/L EDTA pH 8, 100 mmol/L NaCl, 1% polyvinylpyrrolidone, and centrifuged for 5 minutes (12,700 rpm; 4°C). This washing procedure was repeated twice and the resulting supernatants were pooled.

Nucleic acids were precipitated by adding 1 mL of isopropanol in each tube. Samples were stored overnight at 4°C. After centrifugation for 1 hour (12,700 rpm; 4°C), pellets were dissolved in 450 μ L phosphate buffer (Na_2HPO_4 , pH 8, 0.1 mol/L) and 50 μ L potassium acetate (5 mol/L acetate, 3 mol/L potassium) for 90 minutes at 4°C and then centrifuged (30 min; 12,700 rpm; 4°C). Supernatants were transferred in a sterile tube with 2 μ L RNase (10 mg/mL). Tubes were incubated for 30 minutes at 37°C. A total of 50 μ L of sodium acetate and 1 mL of 100% ethanol was added and tubes were mixed gently. After being stored overnight at -20°C, tubes were centrifuged for 1 hour (12,700 rpm; 4°C). The resulting pellet was washed with 1 mL of ethanol (70%) and centrifuged for 5 minutes (12,700 rpm). The supernatant was discarded and the washing procedure was repeated once. Once dried, up to 100 μ L of 10 mmol/L Tris Cl pH 8, 1 mmol/L EDTA pH 8 was added to each tube to dissolve the purified DNA. DNA was stored at -20°C until further analysis.

Microbial Composition Assessment

Quality filtering was performed using SDM software.⁶ Reads were filtered further for minimal and maximal length, any ambiguous nucleotides, barcode and primer errors, and homopolymeric nucleotide runs. The default criteria parameter adapted to the 454 sequencing platform were provided by LotuS. High-quality sequence criterion (read average quality, 27; minimal sequence length, 250; no ambiguous bases, maximum of homopolymer, 8; no mismatch allowed in primers barcode and primers, windows quality threshold average of 25 from quality window of 50 bases) was used to build OTUs. High-quality and midquality sequences were mapped to count the occurrence of established OTUs in a single sample. OTU clustering at 97% identity was performed with UPARSE, which embedded UCHIME as chimera reads filterer. Each representative OTU sequence was aligned and taxonomically assigned using Greengenes database³⁴ (release version 13.8, August 2013) and RDP II database³⁵ (release version 11).

OTU Prevalence and Phylogenetic Assessment

The prevalence of each OTU from the gut microbiota signature for IBS severity was estimated in both healthy subjects and severe IBS patients, and was defined as the proportion of subjects for whom a specific OTU was detected. The prevalence of each OTU in severe IBS patients then was subtracted from the prevalence of the same OTU in healthy subjects. Hence, OTUs with a positive value were enriched in healthy subjects, and OTUs with a negative value were enriched in severe IBS patients. To assess the phylogenetic relationship between OTUs, pairwise nucleotide sequence identities were computed between OTU representative sequences using the SeqinR R package.⁷ A principal coordinate analysis then was performed to assess the phylogenetic specificity of the signature.

Co-inertia Analysis and RV Coefficient

Co-inertia analysis is an ordination method for coupling 2 (or more) sets of parameters (eg, clinical parameters and

microbiota OTU proportion) by looking at their linear combinations. Thus, co-inertia analysis enables the simultaneous ordination of several tables. Co-inertia analysis is related to other multivariate analyses such as canonical correlation analysis. In the case of co-inertia analysis, the co-inertia (the sum of the square of covariance) between the 2 sets is maximized and decomposed. Hence, the co-inertia value is a global measure of the co-structure between the 2 data sets. Co-inertia is high when the 2 sets vary together and low when they vary independently.⁸

Depending on the data set, co-inertia analysis is coupled with principal component analysis or correspondence analysis. In this study, we used co-inertia analysis for 2 types of data set coupling: (1) 2 independent principal coordinate analyses were computed based on fecal and mucosal microbiota composition using JSD distance metric and then subjected to a co-inertia analysis (Figure 1); and (2) principal component analysis were computed on microbiota OTU signatures for IBS severity and successively coupled with a principal component analysis computed from clinical parameters (Figure 5), diet, and medication intake.

The overall relatedness of the 2 data sets was measured by the RV coefficient.⁸ The RV coefficient is the coefficient of correlation between 2 tables (eg, in this study, between the 2 fecal and mucosal microbiota JSD distance matrices). A Monte Carlo test was used to test the robustness of the RV coefficient.

Statistical Modeling By Machine Learning

We used a custom pipeline in R (R version 3.10) to extract the most discriminative features from fecal microbiota OTU composition to distinguish patients with severe IBS from the mild or moderate IBS and healthy controls. Here, we used the LASSO logistic regression classifier⁹ implemented in LIBLINEAR,¹⁰ similar to Zeller et al,¹¹ because it generates a parsimonious classification model that selects only a few features out of a potentially very large set.

Briefly, our pipelines were as follows (see Zeller et al¹¹ for more details).

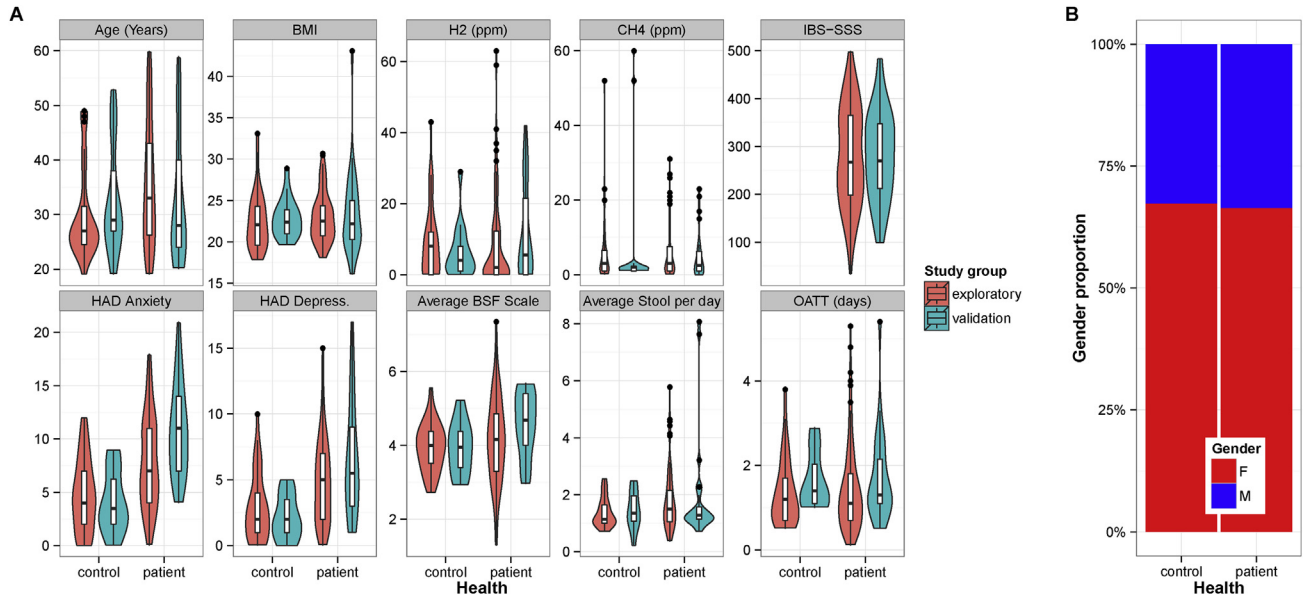
1. Feature transformation: we applied a log-transformation and subsequently standardized features (by centering to mean 0 and dividing by each features' SD to which we added the 10th percentile of SDs across all features).
2. Partitioning data for 10-fold stratified cross-validation (we resampled data set partitions 10 times to obtain more stable accuracy estimates).
3. Fitting a LASSO model on the training data of each cross-validation fold: the LASSO hyperparameter was optimized for each model in a nested 5-fold cross-validation on the training subset using the area under the precision-recall curve as model selection criterion and also enforcing at least 5 nonzero coefficients.
4. Application of the trained LASSO models to obtain the corresponding cross-validation test predictions.

Because of the resampled cross-validation (and also in external validation), there were several test predictions for each test examples. To obtain a single prediction score per example, we averaged all test predictions (from 10 or 100 models in cross-validation or external validation, respectively).

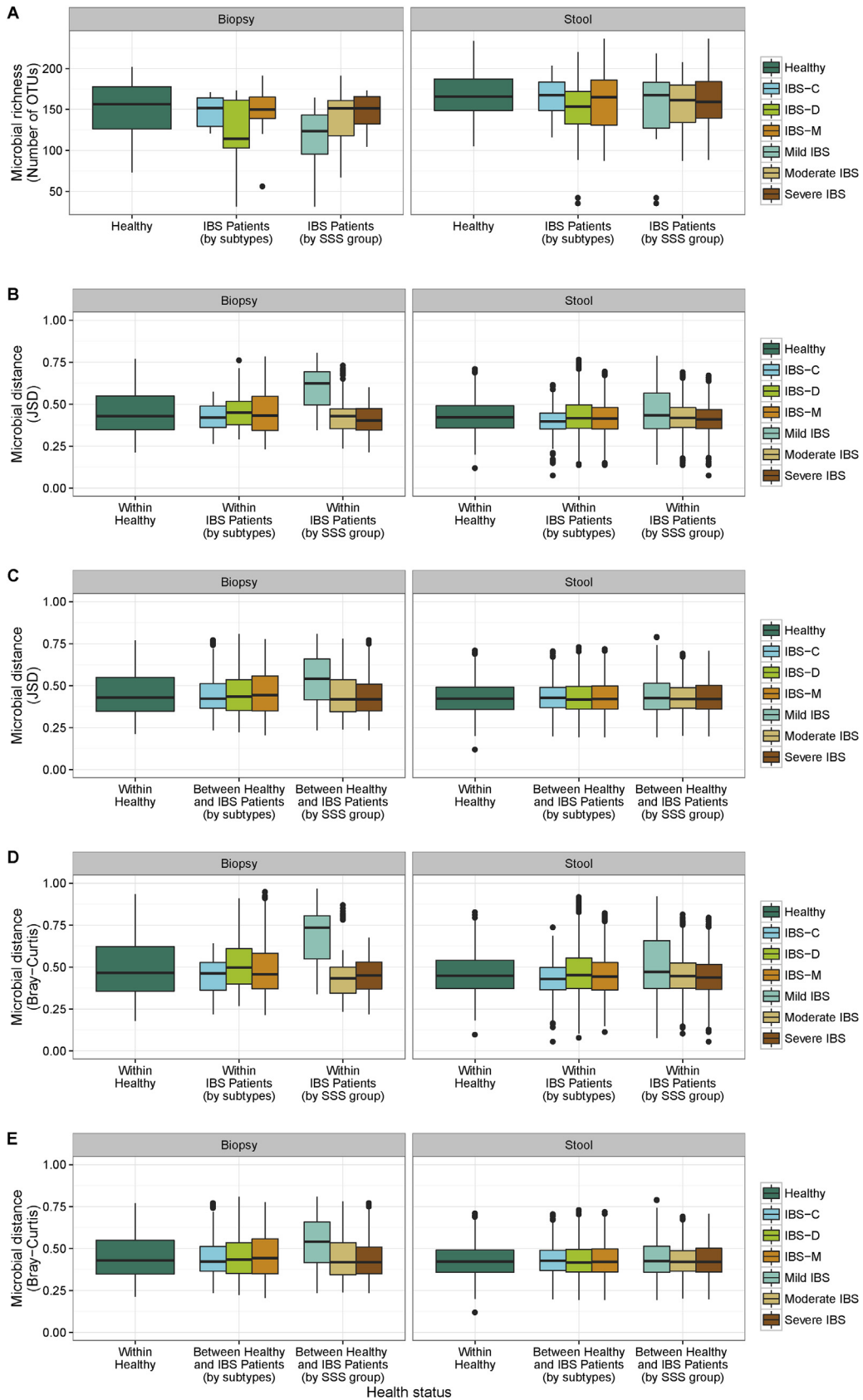
5. Model evaluation using AUROC analysis: 10-fold cross-validation repeated 10 times, we obtained the mean test prediction scores, which we subjected to model performance analysis (Figure 3).
6. Model interpretation and marker extraction: features (bacterial OTUs) with potential association with IBS severity were extracted as nonzero coefficients from all 100 LASSO models (trained in 10 times resampled 10-fold cross-validation).

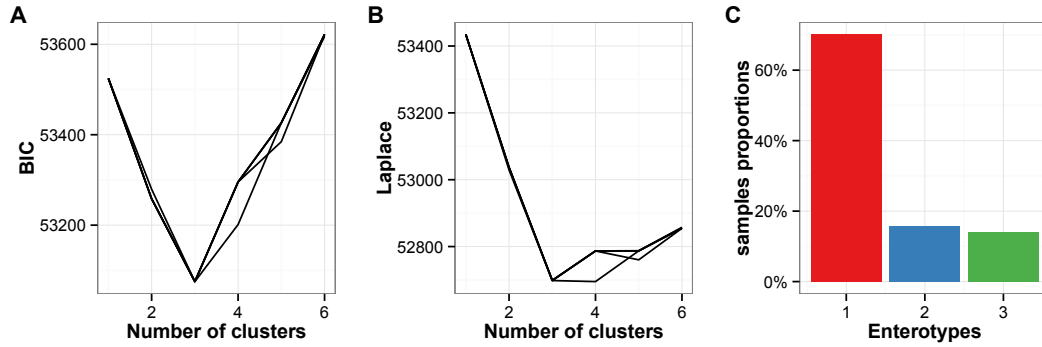
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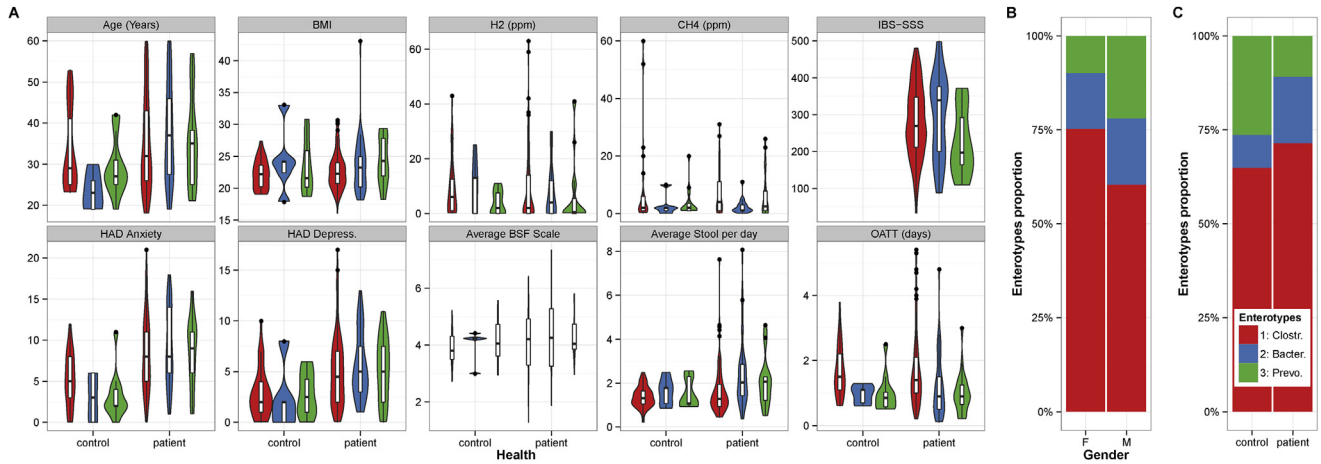
Supplementary Figure 1. Clinical and demographic distribution characteristics for IBS patients and healthy subjects in the 2 study cohorts. (A) Density probability is represented by a *violin plot* and interquartile range is represented by *boxplot* in white. No difference was observed between the exploratory and validation set. As expected, without correction for test multiplicity, HAD anxiety and Depression scores were higher in IBS patients than in healthy subjects ($P < .05$). (B) Gender distribution in healthy subjects and IBS patients ($P > .05$). BSF, Bristol Stool Form.



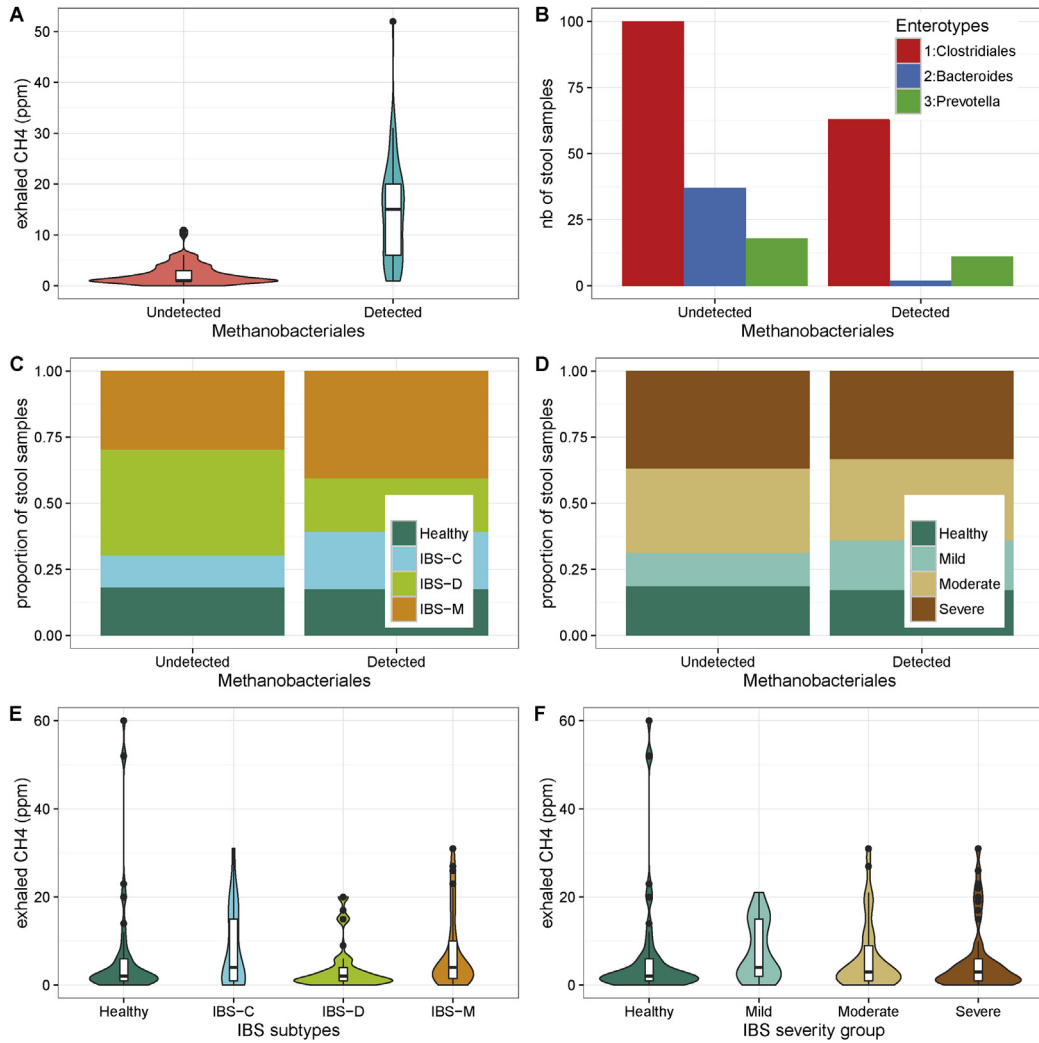


Supplementary Figure 3. Identification of enterotype clusters using Dirichlet multinomial mixture. Optimum number of clusters in the microbiota data set with (A) Laplace and (B) Bayesian information criterion parameters. (C) Proportion of enterotypes in the exploratory set. BIC, Bayesian information criterion.

← **Supplementary Figure 2.** α - and β -diversity in fecal and mucosal microbiota across IBS subtypes and severity in gut microbiota. (A) Microbial richness. No differences were observed between groups. (B) β -diversity calculated with JSD metrics. No differences were observed between groups except for IBS subtype for which mucosal microbiota from mild IBS subtype harbored lower richness than mucosal microbiota from other subtypes. (C) β -diversity calculated with JSD metrics. No difference was observed between groups. (D, E) β -diversity calculated with Bray-Curtis metrics. No difference was observed between groups.



Supplementary Figure 4. Variation of clinical data within enterotypes among healthy subjects and IBS patients. (A) Quantitative variables are represented regarding health status and enterotype stratification. Red, blue, and green accounted for Clostridiales-, *Bacteroides*-, and *Prevotella*-enriched enterotypes, respectively. OATT was faster in *Prevotella* enterotypes compared with other enterotypes in healthy subjects and in IBS patients ($P < .05$). No differences were observed for other parameters ($P > .05$). (B) Enterotype proportions in men and women ($P < .05$). (C) Enterotype proportions in healthy subjects and IBS patients ($P < .05$).



Supplementary Figure 5. Association of Methanobacteriales with microbiota data and clinical data. (A) Exhaled CH₄ as a function of Methanobacteriales presence ($P < .05$). (B) Proportion of samples in enterotypes when Methanobacteriales were detected or not ($P < .05$) (C) Proportion of healthy subjects and IBS subtype samples based on detection of Methanobacteriales ($P < .05$). (D) Proportion of healthy subjects and IBS severity samples based on detection of Methanobacteriales ($P < .05$). (E) Exhaled CH₄ as a function of IBS subtypes. (F) Exhaled CH₄ as a function of IBS severity. Density probability is represented by a violin plot and interquartile range is represented by boxplot in white.