Is it feasible to investigate Lyme disease (LD) symptoms with a conversational AI remote monitoring system, as with other diseases [1]?

Are speech biomarkers able to discriminate between people with and without a diagnosis of LD?

LD is the most common vector-borne illness in the US.
Symptoms can include fatigue, brain fog, and joint pain.
Post-treatment sequelae are not well understood.
There have been some past non-speech biomarker studies [2,3,4].
This is the first known exploration of speech biomarkers of LD.

30 patients diagnosed with LD at the California Center for Functional Medicine, in collaboration with Dr. Sunjya Schweig.
135 healthy controls, collected in collaboration with EverythingALS.
All participants participated in a self-administered speech assessment using a web-based multimodal dialogue system (See Fig 1).
Structured exercises to elicit different types of speech: read speech (short and long), automatic speech (counting), measure of diadochokinesis (DDK), spontaneous speech, and sustained vowel.
Speech metrics were automatically extracted (See Table 1).
Kruskal-Wallis tests were used to plot effect sizes of metric values between the control and patient cohorts.

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Table 1: Automatic speech metrics, depending on task.

<table>
<thead>
<tr>
<th>Domain</th>
<th>Metrics</th>
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<tbody>
<tr>
<td>Energy</td>
<td>Intensity, signal-to-noise ratio, shimmer.</td>
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<tr>
<td>Timing</td>
<td>Speaking and articulation duration, rate; percent pause time (PPT); canonical timing alignment (CTA); syllable rate, count, cycle-to-cycle temporal variation (cTV).</td>
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<tr>
<td>Voice quality</td>
<td>Cepstral peak prominence, harmonics-to-noise ratio.</td>
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<tr>
<td>Frequency</td>
<td>Fundamental frequency mean, min, max, and standard dev.; first three formants; slope of 2nd formant; jitter.</td>
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</table>

Significant cohort differences were seen in the read text tasks for jitter, shimmer, speaking duration and rate, percent pause time (PPT), F0 stdev, canonical timing alignment (CTA) (See Fig. 2).
When age and sex matched, articulation duration and rate showed up jitter remained significant (See Fig 3).

Objective speech metrics extracted from read speech showed differences between patients and controls.
Suggestive evidence of timing related differences.
Stronger evidence of vocal fold behavior differences: LD patients exhibited a smaller range of F0 and a higher rate of jitter.
Could these be Indications of vocal fold dysfunction? [5]

References