# WATCH-SS: Developing a Trustworthy and Explainable Modular Framework for Detecting Cognitive Impairment from Spontaneous Speech

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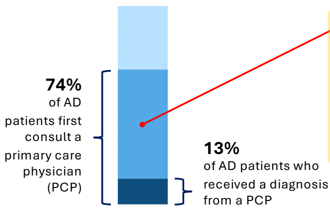
## Introduction

- 7.2 million Americans age 65 and older are estimated to be living with Alzheimer's disease (AD) in 2025[1]
- Over 50% of patients with Alzheimer's disease and related dementias (ADRD) are **undiagnosed** or **unaware of diagnosis**[2]
- Disparities in AD diagnosis and treatment disproportionately affect underrepresented racial, ethnic, and socioeconomic groups[3]
  - E.g., AD is almost twice as prevalent in Black individuals than White individuals (~19% vs 10%), yet Black individuals comprise < 3% of participants in two pivotal new medication trials
- Primary care is an optimal setting for early detection of ADRD
  - Often the first point of contact for emerging health concerns
  - Long-standing relationship with patient may reveal subtle signs (e.g., medication or appointment adherence)
- Key challenges to ADRD diagnosis in primary care:
  - Time/Competing priorities
  - Lack of expertise
  - Lack of comfort with diagnosis or providing follow-up care
  - Lack of support (e.g., access to neurologists)

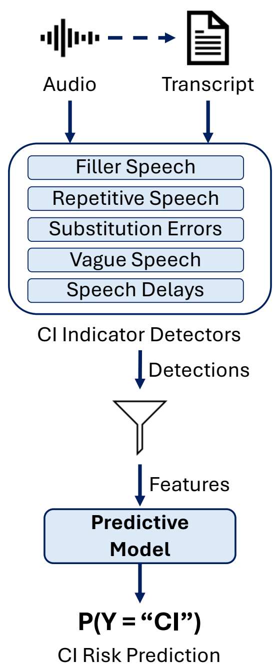



**Goal**: To close this gap with **WATCH-SS**, a screening tool that **passively analyzes patient speech** to alert PCPs to patients who would benefit from a **formal cognitive assessment**.

[1] 2025 Alzheimer's Disease Facts and Figures. Alzheimer's Association. 2025.
[2] H. Amjad, et al. Journal of General Internal Medicine. 2018.
[3] B. Cavedoni and K. O'Brien. Practical Neurology. 2025.

## Methods

### The Warning Assessment and Alerting Tool for Cognitive Health using Spontaneous Speech (WATCH-SS) Framework



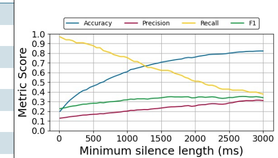

- DementiaBank ADReSS dataset: recordings of subjects performing a standardized picture description task
- For linguistic indicators, we compared two approaches:
  1. **Traditional NLP** (e.g., keyword search, n-gram analysis)
  2. **Large Language Models (LLMs)** (zero- or few-shot prompting with GPT-4o)
- For speech delays, we use a **silence detector** on the audio waveform
- Detections aggregated into **clinically interpretable set of summary features** provided to a **LightGBM** model to produce the final risk prediction

## Results

### Detector Performance

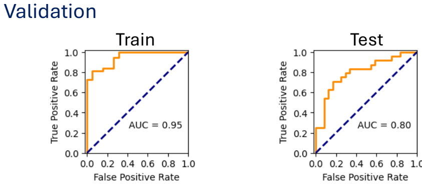
- Simple NLP baselines achieve best performance for lexically-defined tasks like filler and repetitive speech
- LLMs were superior for more semantically complex tasks
- The silence detector for speech delays achieved a peak F1-score of 35%

| Indicator | Detector | Precision | Recall | F1 |
|---|---|---|---|---|
| Filler Speech | Keywords | **0.941** | 0.935 | **0.938** |
| | LLM | 0.623 | **0.941** | 0.750 |
| Repetitive Speech | Unigrams | **0.557** | **0.957** | **0.704** |
| | LLM | 0.407 | **0.957** | 0.571 |
| Substitution Errors | MLM | 0.049 | **0.720** | 0.093 |
| | LLM | **0.107** | 0.640 | **0.184** |
| Vague Speech | Keywords | 0.032 | **0.875** | 0.061 |
| | LLM | **0.061** | **0.875** | **0.115** |




### Model Performance

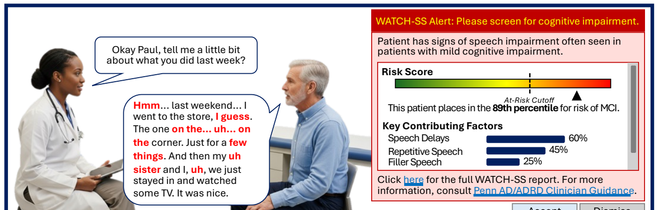
#### Internal Validation




#### External Validation

- On a set of 27 clinic visit recordings for patients 65+ from the OBSERVER Repository, WATCH-SS yielded lower predictive performance (AUC = 0.63), highlighting the challenge of using fragmented patient speech samples common in primary care

## Clinical Use Case




## Conclusion

- WATCH-SS demonstrates that a modular, feature-based approach can achieve strong predictive performance (AUC=80%) while maintaining the interpretability required for a trustworthy, clinically-usable screening tool for cognitive health
- **Future Work**: (i) Refine and expand the set of detectors, (ii) retrain the predictive model on larger, more diverse datasets, and (iii) larger-scale validation study using real clinic visits

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