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

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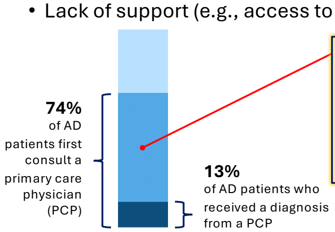
Introduction

- 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)

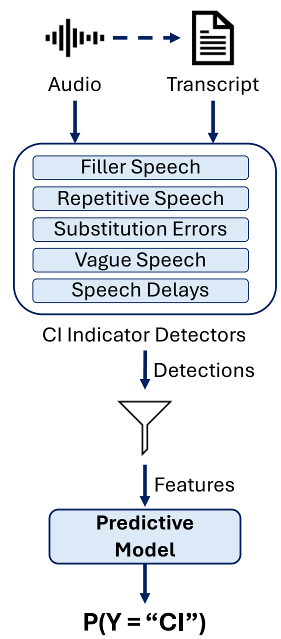


Goal: To close this gap with **WATCH-SS**, a screening tool that **passively analyzes patient speech** to alert PCPs to patients who would benefit from a **formal cognitive assessment**.

[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



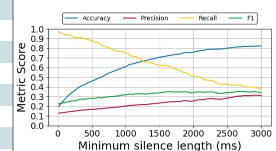
- DementiaBank ADReSS dataset: recordings of subjects performing a standardized picture description task
- For linguistic indicators, we compared two approaches:
  1. **Traditional NLP** (e.g., keyword search, n-gram analysis)
  2. **Large Language Models (LLMs)** (zero- or few-shot prompting with GPT-4o)
- 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

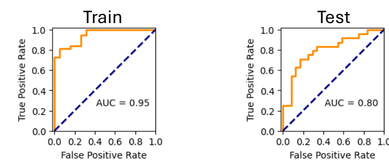
- Simple NLP baselines achieve best performance for lexically-defined tasks like filler and repetitive speech
- LLMs were superior for more semantically complex tasks
- The silence detector for speech delays achieved a peak F1-score of 35%

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

Acknowledgements

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