



Role of Voice Signal Analysis in Screening for Cognitive Impairment: A Study on Community-dwelling Older Adults

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Abstract

This study investigated the potential of voice signal analysis for the early detection of cognitive impairment in community-dwelling older adults. The “Voice Sensor” technology, integrated into the “Malg-eun Village” platform, was evaluated by comparing its predictions with traditional cognitive assessments, including the Korean Mini-Mental State Examination-2. Between January 22, 2024, and May 31, 2024, voice data were collected from 200 participants in Jecheon City, comprising 100 individuals with cognitive impairment and 100 cognitively normal individuals. Voice recordings were gathered through bi-weekly caregiver calls and weekly AI-driven calls. The cognitive status was assessed based on the cumulative voice scores. Statistical analysis included sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV). A t-test was conducted to compare the voice scores between groups, and correlation analysis validated the relationship between the voice sensor results and cognitive assessment scores. The voice sensor showed moderate sensitivity (72.41%) and specificity (63.46%) in detecting cognitive impairment. In particular, it showed a high NPV (89.19%), highlighting its ability to rule out cognitive decline. Nevertheless, its PPV (35.59%) and specificity reveal areas for refinement. These findings suggest that voice signal analysis is a promising, non-invasive, and scalable tool for early cognitive screening in community settings.

Keywords: Cognitive dysfunction; Early diagnosis; Voice sensor

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INTRODUCTION

The growing prevalence of cognitive impairment and dementia in aging populations presents a significant challenge to public health. According to the World Health Organization, over 55 million people globally are living with dementia, a number projected to double every 20 years as populations age [1]. Early detection and intervention in cognitive decline are critical for improving patient outcomes and managing the

social and economic burdens associated with these conditions [2, 3]. Traditional diagnostic methods, such as the Mini-Mental State Examination (MMSE) [4–6], are widely used but can be time-consuming and resource-intensive, particularly when applied to large populations [7–9].

Recent technological advancements have introduced non-invasive and cost-effective approaches to cognitive screening. One promising development is the use of voice signal analysis for early detection of cognitive impairment [10–13].

Aging has been shown to significantly affect auditory processing, which is closely linked to cognitive functions, making voice-based screening a particularly relevant approach [14]. Voice analysis leverages artificial intelligence (AI) and machine learning to detect subtle changes in speech patterns that may indicate cognitive decline [15–18]. This approach offers the potential for widespread, accessible screening, particularly in community settings. The current study explores the effectiveness of the “Voice Sensor” technology developed by Baikal AI, integrated into the “Malg-eun Village” platform, as a tool for screening cognitive impairment in older adults. This platform not only allows for efficient data collection through voice analysis but also incorporates multiple physiological signals such as heart rate and oxygen saturation. Considering that modifiable risk factors play a crucial role in cognitive decline, a multi-modal approach like this can provide valuable insights into preventive strategies for dementia [19]. By evaluating the predictive accuracy of the voice-based screening tool against standard cognitive assessments like the MMSE, this research aims to validate the tool’s usefulness in real-world applications.

This study focuses on a population of elderly individuals in the city of Jecheon, where both voice data and physiological signals were collected to assess the effectiveness of the multi-modal screening approach. The goal is to determine whether the voice signals can provide a reliable, non-invasive method for early cognitive health screening, thus offering a scalable solution for community-based care.

MATERIALS AND METHODS

1. Study Design and Participants

This study was conducted between January 22, 2024, and May 31, 2024, to assess the effectiveness of a voice signal-based screening tool, “Voice Sensor,” developed by Baikal AI, integrated into the “Malg-eun Village” platform (Figure 1). The primary goal was to evaluate the ability of this tool to screen for cognitive impairment in elderly individuals and compare its results with standard cognitive assessments such as the Korean Mini-Mental State Examination-2 (K-MMSE-2) and its variant, the K-MMSE-KC, a subtest from the Korean version of the Consortium to Establish a Registry for Alzheimer’s Disease Assessment Packet (CERAD-K) battery. The study targeted older adults residing in Jecheon City, a community setting with a significant elderly population.

A total of 200 participants were recruited, with 100 individuals predicted to have cognitive impairment and 100 identified as cognitively normal. The classification was based on prior clinical assessments using MMSE scores. Cognitive impairment was defined as an MMSE score below 21, while normal cognitive function was indicated by an MMSE score above 25. Participants were further classified into cognitive impairment prediction groups and normal cognition prediction groups based on their voice signal data.

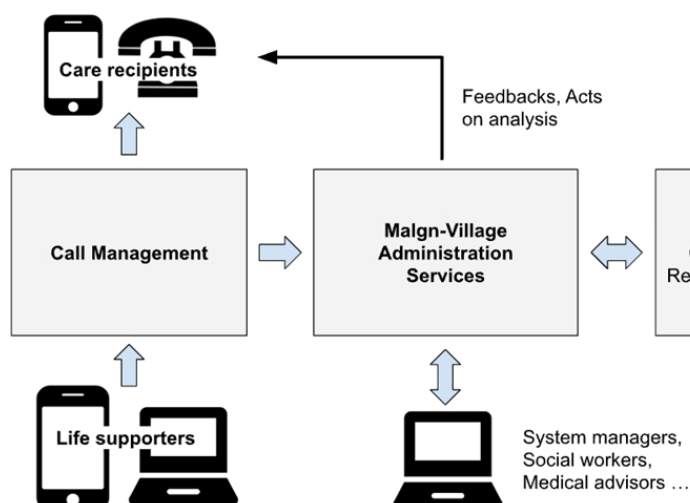


Figure 1. Voice/biomarker processing workflow for cognitive impairment detection in Malg-eun Village.

2. Cognitive Assessments

For cognitive evaluation, the K-MMSE-2 was used as the primary assessment tool for all participants. Additionally, the K-MMSE-KC, a subtest within the CERAD-K battery, was employed to assess a subset of the participants to validate the voice sensor predictions [7]. This included 19 participants tested with K-MMSE-2 and 81 participants tested with K-MMSE-KC.

All cognitive assessments were administered by trained personnel from Jecheon Welfare Foundation and Jecheon Dementia Care Center. These personnel had completed relevant training on the cognitive tools used in this study.

3. Voice Data Collection

Voice Sensor technology was used to collect and analyze voice data. The voice data collection was integrated into the Malg-eun Village platform, where participants engaged in regular phone conversations. Voice data was recorded through two mechanisms as below.

1) Caregiver Calls

Caregivers placed bi-weekly calls to elderly participants as part of the personalized care service, and the conversations were automatically recorded via the Malg-eun Village app.

2) AI Care Calls

An AI system placed weekly automated calls to the participants, and these calls were also recorded and analyzed by the platform.

Voice data were collected over several weeks, with participants averaging 7.3 calls, each lasting about 79 seconds. The data focused on features such as voice clarity, fluency, and pitch, which the Voice Sensor analyzed to predict cognitive impairment by identifying speech irregularities that could correlate with cognitive decline.

4. Statistical Analysis

Statistical analyses were conducted using R software (version 4.3.1; R Development Core Team). To assess the efficacy of the voice sensor technology, we employed a series of statistical measures aimed at determining the accuracy of this tool in identifying cognitive impairment among the el-

derly. Specifically, we calculated sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV) as follows: 1) the proportion of actual cognitive impairment cases correctly identified by the voice sensor (sensitivity); 2) the proportion of cognitively normal participants correctly classified as normal by the voice sensor (specificity); 3) the proportion of participants predicted to have cognitive impairment who were confirmed as impaired based on standard cognitive assessments (PPV); and 4) the proportion of participants predicted to be cognitively normal who were confirmed as normal (NPV).

A t-test was performed to compare the mean voice scores between the cognitively impaired group and the cognitively normal group. A *P*-value less than 0.05 was considered statistically significant. Additionally, a correlation analysis between voice sensor results and K-MMSE-2/K-MMSE-KC scores was conducted to validate the predictive accuracy of the voice sensor technology.

5. Ethical Considerations

All participants provided written informed consent prior to participation in the study. The study protocol was approved by the Institutional Review Board (IRB) of Korea National University of Transportation. Confidentiality and anonymity of all participants were strictly maintained throughout the study. Participants were informed of their right to withdraw from the study at any point without consequence.

RESULTS

1. Participant Demographics

A total of 200 participants were included in the study, divided equally between two groups: 100 individuals predicted to have cognitive impairment, and 100 individuals predicted to be cognitively normal based on the Voice Sensor analysis. The mean age of the cognitively normal prediction group was 74.26 years (± 7.54), while the mean age of the cognitive impairment prediction group was 78.49 years (± 6.40). The cognitively normal prediction group consisted of 35 males and 65 females, while the cognitive impairment prediction group consisted of 44 males and 56 females. Table 1 provides a summary of the participants' demographics.

2. Cognitive Assessment Results

The cognitive status of the participants was confirmed using the K-MMSE-2 and K-MMSE-KC assessments. In the cognitive impairment prediction group (n=100), 21 participants were confirmed to have cognitive impairment (MMSE<21), while 38 participants were classified as cognitively normal (MMSE>25). In the cognitively normal prediction group (n=100), 66 participants were confirmed to be cognitively normal (MMSE>25), while 8 participants were identified as cognitively impaired (MMSE<21). These results are summarized in Table 2.

3. Voice Sensor Predictive Accuracy

The Voice Sensor technology demonstrated a moderate ability to predict cognitive impairment: the voice sensor correctly identified 21 of the 29 participants with confirmed cognitive impairment, demonstrating a sensitivity of 72.41%. This indicates that the tool was able to accurately detect cognitive impairment in most cases. Of the participants predicted to be cognitively normal by the voice sensor, 66 out of

104 were correctly identified as normal, yielding a specificity of 63.46%. Among the participants predicted to have cognitive impairment, 35.59% were confirmed to have cognitive impairment based on the K-MMSE-2 and K-MMSE-KC assessments. Among the participants predicted to be cognitively normal by the voice sensor, 89.19% were confirmed to be cognitively normal based on the K-MMSE-2 and K-MMSE-KC results. This high NPV suggests that the tool is more reliable in confirming normal cognitive status. These results are presented in Table 3.

4. Statistical Analysis and Summary of Key Findings

A t-test was conducted to compare the mean voice scores between the two groups: the cognitive impairment prediction group and the cognitively normal prediction group. The cognitive impairment prediction group had a significantly lower mean voice score (mean=55.3, standard error [SE]=11.5) compared to the cognitively normal prediction group (mean=59.4, SE=13.8), with a *P*-value less than 0.05, indicating a statistically significant difference between the two groups (Table 4). Additionally, a correlation analysis between the Voice Sensor results and the K-MMSE-2/K-MMSE-KC scores revealed a moderate positive correlation (*r*=0.501, *P*<0.05). This finding suggests that the voice sensor technology provides a reasonable approximation of cognitive function as measured by standard cognitive tests.

The voice signal-based screening tool demonstrated moderate sensitivity and specificity in predicting cognitive im-

Table 1. Demographic characteristics and comparison between cognitively normal and cognitive impairment prediction groups

Group	Cognitively normal prediction	Cognitive impairment prediction
Total participants	100	100
Age (yr)**	74.26±7.54	78.49±6.40
Sex distribution (male, female)	35, 65	44, 56
Years of education*	7.18±4.97	5.80±4.66

n or mean±SD.

P*<0.05, *P*<0.001.

Table 2. Confirmation of cognitive status based on K-MMSE-2 and K-MMSE-KC assessments

Group	Cognitive impairment (MMSE<21)	Cognitively normal (MMSE>25)
Cognitive impairment prediction	21	38
Cognitively normal prediction	8	66

Abbreviations: K-MMSE-2, Korean Mini-Mental State Examination-2; K-MMSE-KC, Mini-Mental State Examination in the Korean Version of the CERAD Assessment Packet; CERAD, Consortium to Establish a Registry for Alzheimer's Disease; MMSE, Mini-Mental State Examination.

Table 3. Performance of the "Malg-eun Village" platform in predicting cognitive status

Measure	Result (%)
Sensitivity	72.41
Specificity	63.46
Positive predictive value	35.59
Negative predictive value	89.19

Table 4. Comparison of mean voice scores between cognitive impairment prediction and cognitively normal groups

Analysis	Cognitive impairment prediction group	Cognitively normal prediction group	<i>P</i> -value
Voice score	55.3±11.5	59.4±13.8	<0.05

Mean±SE.

pairment. Notably, the tool's high NPV (89.19%) underscores its potential utility in ruling out cognitive impairment in large-scale screenings. Furthermore, the integration of voice and physiological signals showed promise in enhancing predictive accuracy, although additional research is necessary to refine this multi-modal approach.

The results collectively indicate that while the Voice Sensor technology exhibits potential for large-scale, non-invasive cognitive screening, further development is needed to improve its PPV and overall diagnostic accuracy.

DISCUSSION

The final research subject aimed to evaluate the effectiveness of voice signal analysis technology in the early detection of cognitive impairment among community-dwelling older adults. This study utilized the "Voice Sensor" technology integrated into the "Malg-eun Village" platform and compared its predictive performance with standard cognitive assessment tools such as the K-MMSE-2 and K-MMSE-KC. A total of 200 elderly participants residing in Jecheon City were enrolled, with 100 classified as cognitively impaired and 100 as cognitively normal. Data collection involved voice signal recordings gathered through bi-weekly caregiver calls and weekly AI-driven calls, as well as physiological data, such as heart rate and oxygen saturation, employing a multi-modal screening approach. The analysis focused on predicting cognitive impairment based on voice signal data, validated against K-MMSE results. Statistical metrics, including sensitivity, specificity, PPV, and NPV, were used to assess performance. Additionally, a t-test compared the mean voice scores between groups, and a correlation analysis examined the predictive accuracy of the voice sensor in relation to K-MMSE scores.

This study evaluated the effectiveness of the voice signal-based cognitive screening tool, "Voice Sensor," in predicting cognitive impairment among older adults. The results indicate that the tool provides a useful and non-invasive method for early detection of cognitive decline, particularly in community settings. However, while the tool showed promise, several key findings and limitations must be addressed to fully understand its potential in practical applications.

The Voice Sensor demonstrated a sensitivity of 72.41%, indicating that the tool successfully identified most cases of cognitive impairment. This suggests that the technology is capable of detecting early signs of cognitive decline, which is essential for timely intervention. However, the specificity of 63.46% highlights the tool's limitations in correctly identifying cognitively normal individuals. This relatively moderate specificity suggests that a significant proportion of participants without cognitive impairment were incorrectly flagged as at-risk. These false positives may lead to unnecessary follow-up assessments or interventions, increasing the burden on healthcare systems and individuals.

The PPV was found to be 35.59%, meaning that when the tool predicted cognitive impairment, the likelihood of the participant truly having cognitive impairment was only 35.59%. This relatively low PPV indicates that a considerable number of participants were incorrectly identified as cognitively impaired. On the other hand, the NPV was high, at 89.19%, suggesting that the tool was highly effective in ruling out cognitive impairment. In clinical and community settings, this high NPV is advantageous because it can reliably identify individuals who are not at risk, reducing unnecessary interventions for those without cognitive decline.

The findings of this study support the potential of voice signal analysis as an accessible and scalable solution for cognitive screening, particularly in community-based settings. The Voice Sensor technology offers the benefits of being non-invasive, cost-effective, and suitable for large populations, making it an ideal tool for early detection in elderly populations who may not have easy access to traditional cognitive assessments [20–22]. The integration of this tool with platforms such as the Malg-eun Village app, which facilitates regular caregiver and AI-driven calls, enhances its practicality by enabling continuous monitoring of cognitive health.

This study differs from previous research on voice-based cognitive impairment detection in key ways. Earlier studies often focused on the feasibility of voice signal analysis in controlled settings with small-scale datasets. Hajjar et al [23] examined voice biomarkers for early Alzheimer's detection in clinical environments, showing promising results but lacking real-world validation and integration into healthcare platforms. In contrast, our study integrates Voice Sensor

technology into the Malg-eun Village platform, applying it in a community-based setting with a significant elderly population. By utilizing caregiver-initiated and AI-driven calls, this study emphasizes continuous monitoring and naturalistic data collection, reflecting older adults' daily experiences.

However, the moderate specificity and low PPV suggest that the Voice Sensor should not be used as a standalone diagnostic tool. Instead, it may serve as a preliminary screening method, which can identify individuals for further cognitive testing using standardized tools such as the K-MMSE-2 or K-MMSE-KC. By combining voice analysis with conventional cognitive assessments, healthcare providers can improve the accuracy of cognitive decline detection and reduce the rate of false positives.

Several limitations of this study should be considered. First, the sample size, while sufficient for an initial assessment, may limit the generalizability of the findings to broader populations. Future research should include larger and more diverse samples to validate the tool's performance across different demographic groups. Additionally, the integration of physiological data from devices like the Vital Ring showed potential for enhancing predictive accuracy, but further research is needed to optimize the combination of voice and physiological signals for more accurate predictions.

Another area for improvement is the development of more sophisticated algorithms for voice analysis. The current model demonstrated moderate predictive accuracy, but the inclusion of more advanced machine learning techniques could enhance the tool's sensitivity and specificity. Future studies should explore how incorporating additional voice features, such as prosody and fluency, could improve the prediction of cognitive impairment.

Despite its widespread use, the MMSE has its limitations. It is not designed to provide a definitive diagnosis but rather to screen for potential cognitive impairment. The test may not accurately reflect the cognitive abilities of individuals with sensory impairments or those with limited English proficiency. Moreover, while it can indicate the presence of cognitive decline, it cannot determine the underlying cause, which requires a more comprehensive clinical assessment.

Lastly, further investigation into the relationship between specific voice patterns and cognitive function is warranted. This would help refine the voice analysis models and in-

crease the tool's diagnostic precision, particularly in distinguishing between different types of cognitive impairments, such as mild cognitive impairment and Alzheimer's disease.

In conclusion, this study demonstrated that voice signal analysis, as implemented through the Voice Sensor technology, holds promise for early detection of cognitive decline in older adults. The tool's high NPV indicates its utility in identifying individuals unlikely to have cognitive impairment, while the moderate sensitivity suggests its potential for early screening. However, the relatively low PPV and moderate specificity highlight the need for further refinement of the technology.

Future research should focus on improving the tool's accuracy through larger sample sizes, better integration of physiological data, and the development of more advanced algorithms. With these improvements, the Voice Sensor has the potential to become a valuable component of community-based cognitive health screening programs, helping to identify at-risk individuals and facilitate timely interventions.

음성 신호 분석을 통한 인지 장애 선별: 지역 사회 거주 노인을 대상으로 한 연구

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요약

본 연구는 지역 사회에 거주하는 노인의 인지 장애 초기 발견을 위한 음성 신호 분석의 가능성을 조사하였다. “맑은 동네” 플랫폼에 통합된 “보이스 센서” 기술은 전통적인 인지 평가 도구인 한국형 Mini-Mental State Examination-2 (K-MMSE-2/K-MMSE-KC)와 그 예측 성능을 비교하여 평가되었다. 2024년 1월 22일부터 2024년 5월 31일까지, 충청북도 제천시에서 거주하는 200명의 참가자로부터 음성 데이터를 수집하였다. 이들 중 100명은 인지 장애가 예측된 사람들, 100명은 정상 인지가 예측된 사람들로 구성되었다. 음성 녹음은 격주로 진행된 생활지원사의 통화 자동 녹음과 주간 AI 기반 통화를 통해 수집되었으며, 인지 상태는 누적된 음성 점수를 바탕으로 평가되었다. 통계 분석은 민감도, 특이도, 양성 예측 값(PPV), 음성 예측 값(NPV)

을 포함하였다. 또한, 두 그룹 간의 음성 점수를 비교하기 위해 t-검정을 실시하였으며, 음성 센서 결과와 인지 평가 점수 간의 관계를 확인하기 위해 상관 분석을 수행하였다. Voice Sensor는 인지 장애를 감지하는 데 있어 중간 정도의 민감도(72.41%)와 특이도(63.46%)를 보였다. 특히, 높은 음성 예측 값(NPV, 89.19%)을 보여 인지 감소를 배제하는 능력이 뛰어난 것으로 나타났다. 그러나 낮은 양성 예측 값(PPV, 35.59%)과 상대적으로 낮은 특이도는 개선이 필요한 부분을 시사한다. 이러한 결과는 음성 신호 분석이 지역 사회 환경에서 인지 장애의 초기 스크리닝을 위한 유망하고 비침습적이며 확장 가능한 도구가 될 수 있음을 시사한다.

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Conflict of interest

None.

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- Data curation: Lee S.
- Formal analysis: Lee S, Yun G, Lee H.
- Methodology: Youn YC, Kim SY, Jeong HT.
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- Validation: Youn YC, Kim SY, Jeong HT, Kim IJ.
- Investigation: Lee S, Yun G.
- Writing – original draft: Youn YC, Jeong HT.
- Writing – review & editing: Youn YC, Jeong HT, Kim IJ.

Ethics approval

All procedures were performed in accordance with protocols approved by the Korea National University of Transportation Institutional Review Board (Approval numbers: KNUT-2024-HR-37-05).

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REFERENCES

1. World Health Organization (WHO). Dementia [Internet]. WHO [cited 2024 July 1]. Available from: <https://www.who.int/news-room/fact-sheets/detail/dementia>
2. Prince M, Wimo A, Guerchet M, Ali GC, Wu YT, Prina M. World Alzheimer report 2015: the global impact of dementia: an analysis of prevalence, incidence, cost and trends [Internet]. Alzheimer's Disease International [cited 2024 July 1]. Available from: <https://www.alz.co.uk/research/world-report-2015>
3. Livingston G, Sommerlad A, Orgeta V, Costafreda SG, Huntley J, Ames D, et al. Dementia prevention, intervention, and care. *Lancet*. 2017;390:2673-2734. [https://doi.org/10.1016/s0140-6736\(17\)31363-6](https://doi.org/10.1016/s0140-6736(17)31363-6)
4. Mini-Mental State Examination (MMSE) [Internet]. PsychDB [cited 2024 July 1]. Available from: <https://www.psychdb.com/cognitive-testing/mmse>
5. Folstein MF, Folstein SE, McHugh PR. "Mini-mental state": a practical method for grading the cognitive state of patients for the clinician. *J Psychiatr Res*. 1975;12:189-198. [https://doi.org/10.1016/0022-3956\(75\)90026-6](https://doi.org/10.1016/0022-3956(75)90026-6)
6. Crum RM, Anthony JC, Bassett SS, Folstein MF. Population-based norms for the Mini-Mental State Examination by age and educational level. *JAMA*. 1993;269:2386-2391. <https://doi.org/10.1001/jama.1993.03500180078038>
7. Philipps V, Amieva H, Andrieu S, Dufouil C, Berr C, Dartigues JF, et al. Normalized Mini-Mental State Examination for assessing cogni-

- tive change in population-based brain aging studies. *Neuroepidemiology*. 2014;43:15-25. <https://doi.org/10.1159/000365637>
8. Borson S, Scanlan JM, Chen P, Ganguli M. The Mini-Cog as a screen for dementia: validation in a population-based sample. *J Am Geriatr Soc*. 2003;51:1451-1454. <https://doi.org/10.1046/j.1532-5415.2003.51465.x>
 9. Weinmann T, Vetter C, Karch S, Nowak D, Radon K. Shift work and cognitive impairment in later life - results of a cross-sectional pilot study testing the feasibility of a large-scale epidemiologic investigation. *BMC Public Health*. 2018;18:1256. <https://doi.org/10.1186/s12889-018-6171-5>
 10. Ding H, Lister A, Karjadi C, Au R, Lin H, Bischoff B, et al. Detection of mild cognitive impairment from non-semantic, acoustic voice features: The Framingham Heart Study. *JMIR Aging*. 2024;7:e55126. <https://doi.org/10.2196/55126>
 11. Ambrosini E, Cid M, de Isla CG, Salamanca P, Borghese NA, Ferrante S, et al. Automatic speech analysis to early detect functional cognitive decline in elderly population. *Annu Int Conf IEEE Eng Med Biol Soc*. 2019;2019:212-216. <https://doi.org/10.1109/EMBC.2019.8856768>
 12. Konig A, Satt A, Sorin A, Hoory R, Derreumaux A, David R, Robert PH. Use of speech analyses within a mobile application for the assessment of cognitive impairment in elderly people. *Curr Alzheimer Res*. 2018;15:120-129. <https://doi.org/10.2174/1567205014666170829111942>
 13. Bleibel M, El Cheikh A, Sadier NS, Abou-Abbas L. The effect of music therapy on cognitive functions in patients with Alzheimer's disease: a systematic review of randomized controlled trials. *Alzheimers Res Ther*. 2023;15:65. <https://doi.org/10.1186/s13195-023-01214-9>
 14. Pichora-Fuller MK, Souza PE. Effects of aging on auditory processing of speech. *Int J Audiol*. 2003;42 Suppl 2:2S11-2S16. <https://doi.org/10.3109/14992020309074638>
 15. García-Gutiérrez F, Alegret M, Marquíé M, Muñoz N, Ortega G, Cano A, et al. Unveiling the sound of the cognitive status: Machine Learning-based speech analysis in the Alzheimer's disease spectrum. *Alzheimers Res Ther*. 2024;16:26. <https://doi.org/10.1186/s13195-024-01394-y>
 16. Tripathi T, Kumar R. Speech-based detection of multi-class Alzheimer's disease classification using machine learning. *Int J Data Sci Anal*. 2024;18:83-96. <https://doi.org/10.1007/s41060-023-00475-9>
 17. Tracy JM, Özkanca Y, Atkins DC, Hosseini Ghomi R. Investigating voice as a biomarker: deep phenotyping methods for early detection of Parkinson's disease. *J Biomed Inform*. 2020;104:103362. <https://doi.org/10.1016/j.jbi.2019.103362>
 18. Xue C, Karjadi C, Paschalidis IC, Au R, Kolachalama VB. Detection of dementia on voice recordings using deep learning: a Framingham Heart Study. *Alzheimers Res Ther*. 2021;13:146. <https://doi.org/10.1186/s13195-021-00888-3>
 19. Xu W, Tan L, Wang HF, Jiang T, Tan MS, Tan L, et al. Meta-analysis of modifiable risk factors for Alzheimer's disease. *J Neurol Neurosurg Psychiatry*. 2015;86:1299-1306. <https://doi.org/10.1136/jnnp-2015-310548>
 20. Sara JDS, Orbelo D, Maor E, Lerman LO, Lerman A. Guess what we can hear-novel voice biomarkers for the remote detection of disease. *Mayo Clin Proc*. 2023;98:1353-1375. <https://doi.org/10.1016/j.mayocp.2023.03.007>
 21. Agbavor F, Liang H. Artificial intelligence-enabled end-to-end detection and assessment of Alzheimer's disease using voice. *Brain Sci*. 2022;13:28. <https://doi.org/10.3390/brainsci13010028>
 22. Ahn K, Cho M, Kim SW, Lee KE, Song Y, Yoo S, et al. Deep learning of speech data for early detection of Alzheimer's disease in the elderly. *Bioengineering (Basel)*. 2023;10:1093. <https://doi.org/10.3390/bioengineering10091093>
 23. Hajjar I, Okafor M, Choi JD, Moore E 2nd, Abrol A, Calhoun VD, et al. Development of digital voice biomarkers and associations with cognition, cerebrospinal biomarkers, and neural representation in early Alzheimer's disease. *Alzheimers Dement (Amst)*. 2023;15:e12393. <https://doi.org/10.1002/dad2.12393>