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Effectiveness of deep neural networks in hearing aids for improving signal-to-noise ratio, speech recognition, and listener preference in background noise

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Introduction: Traditional approaches to improving speech perception in noise (SPIN) for hearing-aid users have centered on directional microphones and remote wireless technologies. Recent advances in artificial intelligence and machine learning offer new opportunities for enhancing the signal-to-noise ratio (SNR) through adaptive signal processing. In this study, we evaluated the efficacy of a novel deep neural network (DNN)-based algorithm, commercially implemented as Edge Mode™, in improving SPIN outcomes for individuals with sensorineural hearing loss beyond that of conventional environmental classification approaches.

Methods: The algorithm was evaluated using (1) objective KEMAR-based performance in seven real-world scenarios, (2) aided and unaided speech-in-noise performance in 20 individuals with SNHL, and (3) real-world subjective ratings via ecological momentary assessment (EMA) in 20 individuals with SNHL.

Results: Significant improvements in SPIN performance were observed on CNC+5, QuickSIN, and WIN, but not NST+5, likely due to the use of speech-shaped noise in the latter, suggesting the algorithm is optimized for multi-talker babble environments. SPIN gains were not predicted by unaided performance or degree of hearing loss, indicating individual variability in benefit, potentially due to differences in peripheral encoding or cognitive function. Furthermore, subjective EMA responses mirrored these improvements, supporting real-world utility.

Discussion: These findings demonstrate that DNN-based signal processing can meaningfully enhance speech understanding in complex listening environments, underscoring the potential of AI-powered features in modern hearing aids and highlighting the need for more personalized fitting strategies.

KEYWORDS

hearing aids, audiology, speech in noise, deep neural network, artificial intelligence, ecological momentary assessment

Introduction

Approximately 15% of adults in the United States report some difficulty hearing (Blackwell et al., 2014), and by 2050 nearly 2.5 billion individuals are projected to have some degree of hearing loss (Chadha et al., 2021). The most common complaint associated with hearing loss is difficulty communicating in background noise (Pichora-Fuller, 1997; Gatehouse and Noble, 2004; Hannula et al., 2011; Le Prell and Clavier, 2017; Jorgensen and Novak, 2020; Carr and Kihm, 2022). For individuals with sensorineural hearing loss that cannot be treated medically or surgically, hearing aids (HA) are the most common recommendation, and these devices have helped millions of people to hear and communicate more effectively. Despite the many benefits of hearing aids, difficulty understanding speech in noise (SPIN) remains a common complaint. These difficulties (e.g., “they don’t work”) are a common reason given by individuals who obtain hearing aids, and either return them within the trial period, or do not wear them consistently (McCormack and Fortnum, 2013; Hong et al., 2014; Humes, 2003; Hickson et al., 2014; Jilla et al., 2020; Powers and Rogin, 2020; Aazh et al., 2015). Consistent with these self-reports, speech in noise abilities correlate with hearing aid satisfaction (Saunders and Forsline, 2006; Davidson et al., 2021; Walden and Walden, 2004), and are worse in patients who tried and returned hearing aids when compared to individuals who kept their hearing aids (Humes, 2021a). Thus, while hearing aids benefit millions of individuals each year, difficulties with SPIN persist in many patients, leading to dissatisfaction, and even discontinuation in some cases.

Speech in noise abilities not only deteriorate with increasing hearing loss, but are also highly variable between individuals with similar hearing thresholds, even when the signal is audible (Wilson, 2011; Fitzgerald et al., 2023; Smith et al., 2024). These suprathreshold deficits in speech understanding are particularly noteworthy given that current procedures for fitting of hearing aids is focused primarily on maximizing audibility without exceeding uncomfortable loudness levels. This approach is at the heart of prescriptive procedures such as the “Desired Sensation Level” (DSL; Seewald et al., 1985; Scollie et al., 2005; Bagatto et al., 2005), those from the National Acoustics Laboratories (NAL; Byrne and Tonisson, 1976; Byrne and Dillon, 1986; Byrne et al., 2001; Keidser et al., 2011), and with proprietary prescriptive fitting methods developed by hearing aid manufacturers (e.g., Keidser et al., 2003). Thus, addressing the SPIN difficulties faced by patients requires solutions beyond making sounds audible.

Conventional approaches to improving the signal-to noise ratio (SNR) in users of hearing aids has routinely focused on directional microphones or the use of wireless remote microphones (Gnewikow et al., 2009). These approaches, while beneficial in many regards, do not directly manipulate the signal itself in an effort to improve the SNR. Conventional approaches to noise management based on spectral subtraction or modulation-based noise reduction systems are primarily shown to improve listening comfort with little to no improvement in speech understanding (Mueller et al., 2006; Bentler et al., 2008). In recent years, however, there has been a revolution in the use of artificial intelligence (AI) and machine learning (ML) technologies to understand and manipulate auditory signals (Bishop and Nasrabadi, 2006; LeCun

et al., 2015; Zhang et al., 2018; Fabry and Bhowmik, 2021). Deep neural networks have been trained to simulate cochlear and nerve fiber outputs (Baby et al., 2021; Nagathil et al., 2021; Drakopoulos et al., 2021), and to compensate for impaired cochlea (Bondy et al., 2004; Diehl et al., 2023). To date, most ML efforts to improve SPIN abilities attempt to remove noise from the speech to improve the SNR (Soni et al., 2023; Healy and Yoho, 2016; Healy et al., 2017; Zhao et al., 2018; Alexander, 2021; Fischer et al., 2021; Fabry and Bhowmik, 2021). While promising, the integration of these approaches into conventional hearing aids has been limited until recently due to challenges such as the need for specialized computational processing hardware, constraints in power consumption, insufficient training data for these models, and other technological variables (Zou, 2025).

In the present study, our goal was to evaluate the effectiveness of a novel signal processing technique based on deep neural networks. This signal processing algorithm was implemented in a hearing aid feature called Edge Mode™. Here, this algorithm was evaluated in three ways, including (1) objective evaluation of SNR improvements in laboratory testing, (2) clinical evaluation of SNR benefits for individuals with sensorineural hearing loss, and (3) subjective assessment using ecological momentary assessment (EMA) questions during use in their daily life.

Methods

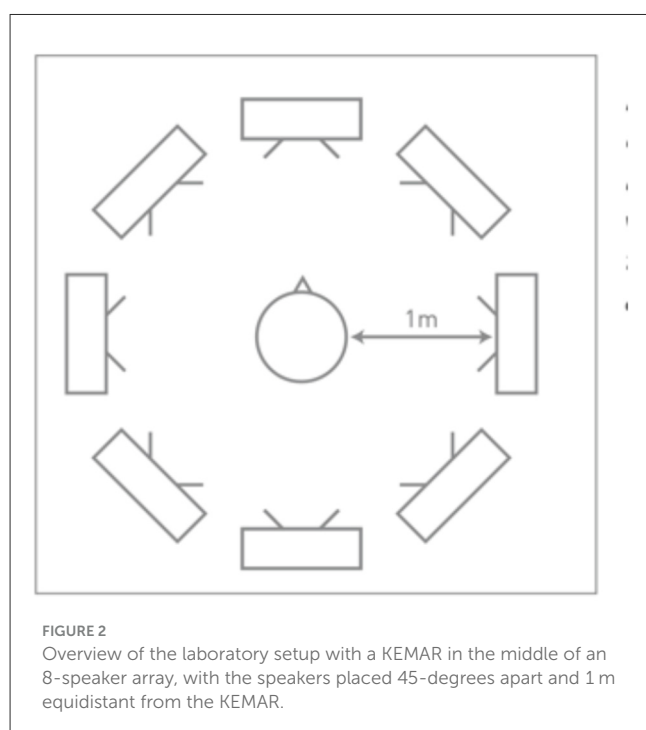
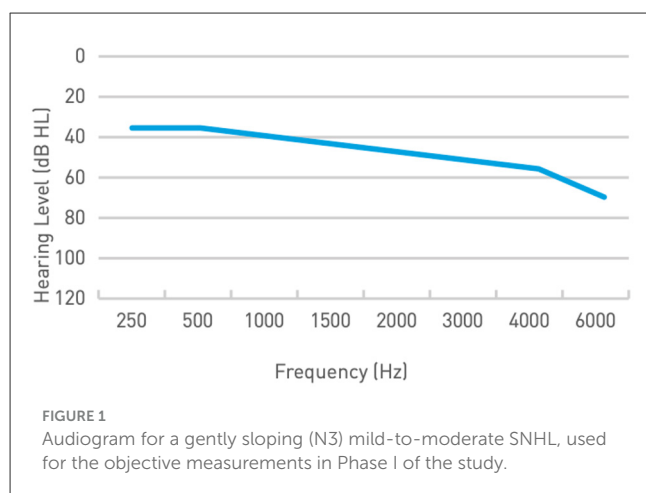
Data were collected in two phases. The first phase consisted of objective laboratory evaluation of changes in the SNR on a KEMAR mannequin. The second phase consisted of both behavioral and subjective data obtained in participants with sensorineural hearing loss. These phases are described below.

Procedures

Phase I

In this phase, changes in SNR with the Edge Mode™ algorithm, relative to the default “Personal” program (Adaptive Directionality enabled with Speech in Noise default setting) were evaluated on a Knowles Electronics Manikin for Acoustic Research (KEMAR) using a pair of Starkey Genesis AI receiver-in-canal (RIC) hearing aids fitted with occluding power dome ear tips. The devices were programmed to meet prescriptive targets for a gently sloping (N3) mild-to-moderate sensorineural hearing loss (Figure 1). The KEMAR was positioned at the center of an 8-speaker array in a sound-treated room, with loudspeakers spaced 45° apart and placed 1 meter away (Figure 2).

Seven acoustic scenes designed to stimulate real-world listening environments were evaluated: bar, shopping mall, restaurant, construction, indoor crowd, outdoor crowd, and city noise. To stimulate diffuse noise, commonly experienced by hearing aid users (Wu et al., 2018), uncorrelated noise snippets from the same recording were played simultaneously from all 8 speakers, with speech presented from the front (0° azimuth) speaker. Each



condition began with 30 s of noise alone, followed by 30 s of speech-in-noise (SPIN). The speech level was fixed at 70 dB SPL and the noise at 73 dB SPL, creating a challenging -3 dB SNR environment. These values were chosen as they approximate conversational speech levels and a SNR that that would normally yield poor speech recognition for individuals with hearing loss or perceived hearing difficulties (Fitzgerald et al., 2023, 2024; Smith et al., 2024; Wilson, 2011).

The “Personal” program uses a machine-learning algorithm to perform acoustic environmental classification (AEC). In this process, the AEC algorithm monitors and categorizes the listening environment into one of the seven acoustic environments listed above. Based on the results of the classification, the program automatically applies necessary hearing aid features (e.g., frequency-specific gain, output limitation, multiple-channel compression, omni and directional microphones, multiple channel

continuous or transient noise management, and wind noise suppression). In contrast, the Edge Mode™ algorithm applies a user-initiated “acoustic snapshot” that provides an additional analysis of the soundscape across the seven acoustic scenes. This analysis results in more aggressive offsets than the default “Personal” program.

The Edge Mode™ algorithm is executed directly on the hearing aid’s processor chip, which features a custom-designed integrated hardware accelerator optimized for deep neural network (DNN) operations under low-power, real-time conditions. As a result, no smartphone or cloud connectivity is required. Figure 3 presents a schematic comparison between traditional noise reduction architectures in hearing aids and the advanced sound-processing framework incorporating onboard DNN processing.

Measurements were made using the Hagerman method (Hagerman and Olofsson, 2004), a well-established procedure that may be used for evaluating hearing aids’ noise reduction systems. It is based on the phase inversion technique, where multiple recordings take place and the phase of one signal is inverted between the measurements. This phase inversion method separates signal and noise at the hearing aid output, enabling accurate calculate of SNR improvement by isolating the processed signals from the recorded mixed signal. For a given condition, Speech Intelligibility Index (SII) computations may be used to estimate the audibility and relative importance of speech information across different bands from Hagerman measurements to calculate SNR and predicted SPIN measurements in humans.

Phase II

In this phase, we determined whether behavioral or subjective improvements were observed in hearing-aid users when Edge Mode™ algorithm was active relative to the default “Personal” program. Here, 20 human participants (11 female) with an average age of 77 years ($SD = 6.8$ years) were recruited from patients seen at the Stanford Ear Institute, or from a residential living facility. Demographic information for this sample is provided in Table 1. All participants first began with pure-tone audiometric assessments, including measurement of air- and bone-conduction thresholds using the modified Hughson-Westlake method (Carhart and Jerger, 1959). Inter-octave thresholds at 3,000 and 6,000 Hz were always obtained, with other inter-octave thresholds measured when thresholds differed by ≥ 20 dB HL between octaves (Wilson and McArdle, 2014).

Unaided speech recognition in background noise was assessing using four speech-in-noise tasks. The first task consisted of Consonant-Nucleus-Consonant (CNC) words (Peterson and Lehiste, 1962). Scores were obtained using a single 50-word list presented in the presence of multi-talker babble with a signal-to-noise ratio (SNR) of $+5$ dB. Performance was scored in percent correct using whole words and individual phonemes. The second measure was the QuickSIN (Killion et al., 2004), which measures the SNR at which 50% of key words in low-context sentences can be repeated in the presence of multi-talker babble. Each QuickSIN list consists of six low-context sentences, with each sentence containing five key words, presented in decreasing SNR steps from $+25$ dB to 0 dB in 5 dB steps (Killion et al., 2004). The third SPIN

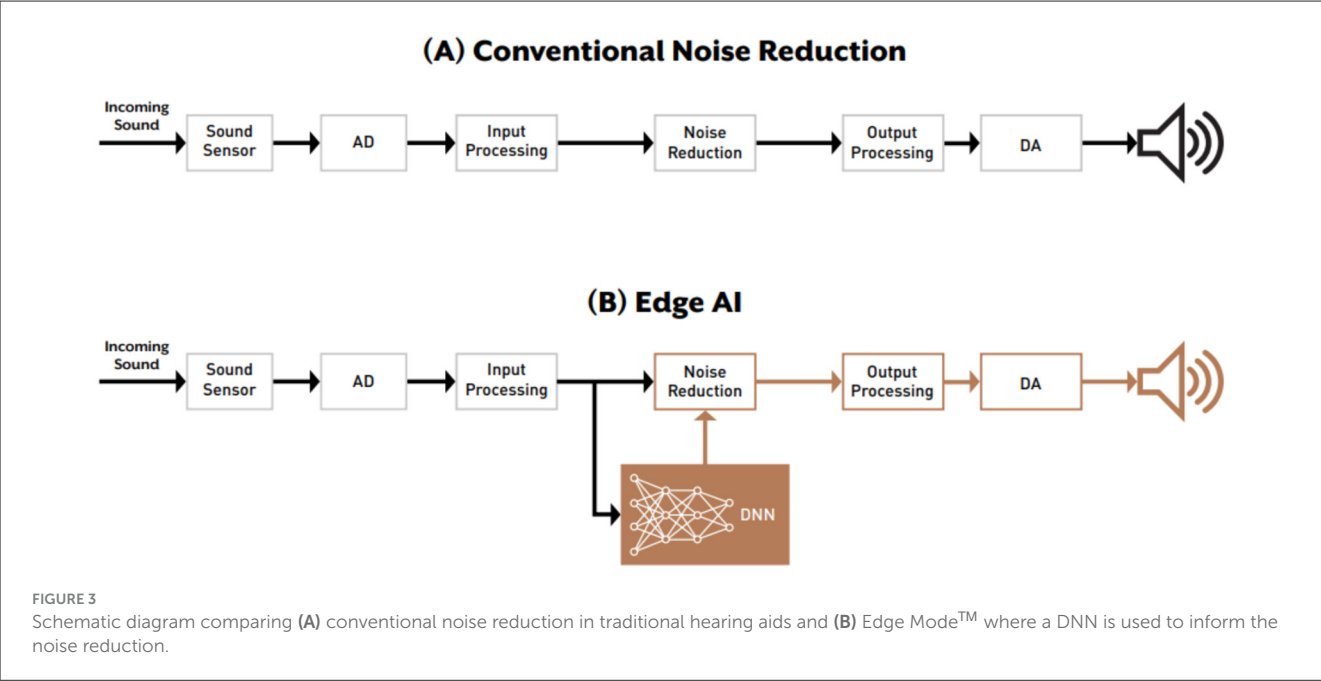


TABLE 1

Participants	Age	Sex	Race/ethnicity	RIGHT: 500 Hz	RIGHT: 1,000 Hz	RIGHT: 2,000 Hz	RIGHT: 4,000 Hz	LEFT: 500 Hz	LEFT: 1,000 Hz	LEFT: 2,000 Hz	LEFT: 4,000 Hz
1	77	Female	White	45	55	60	60	45	55	60	65
2	95	Male	Asian	50	50	55	70	65	60	55	65
3	79	Female	White	25	30	35	50	25	30	40	50
4	68	Female	Asian	30	40	45	40	30	35	40	25
5	82	Female	White	15	30	60	60	15	15	50	65
6	73	Male	Asian	25	35	30	50	35	50	60	75
7	71	Female	White	35	40	45	70	20	25	35	65
8	87	Female	White	35	40	45	40	40	35	50	45
9	75	Male	Asian	20	35	70	65	20	35	65	65
10	70	Male	White	15	15	15	40	25	20	20	50
11	78	Male	White	15	20	35	45	15	15	30	40
12	69	Male	White	20	15	15	70	20	15	25	70
13	79	Male	White	20	30	35	40	20	25	25	50
14	85	Male	White	50	55	65	65	40	25	35	65
15	76	Female	White	20	40	55	50	20	35	50	50
16	78	Male	White	35	35	35	70	35	35	45	55
17	71	Male	White	20	30	55	65	20	25	50	65
18	79	Female	Other	45	55	55	55	35	45	55	60
19	82	Female	White	15	20	30	60	20	15	20	60
20	67	Female	White	25	35	45	60	25	30	40	60
21	80	Female	White	25	40	50	25	25	50	60	45

measure was the Words in Noise (WIN) test (Wilson, 2003; Wilson et al., 2003). In this measure monosyllabic words are presented at different SNR values beginning at +24 dB and decreasing to 0 dB. As with the QuickSIN, the output of this test is the SNR at which 50% of words can be correctly repeated. The final SPIN measure was the Non-sense Syllable Test (NST, Kuk et al., 2010). In this measure, 115 phonetically balanced non-sense words were presented in the presence of continuous speech-weighted noise with a 5 dB SNR, and the percent correct was recorded.

All SPIN assessments were conducted using a three-speaker array centered at 0-, 135-, and 225-degrees azimuth. In all tests, speech was presented at 0 degrees azimuth. In the CNC, WIN and NST tests, the noise was delivered through the 135- and 225-degree azimuth speakers. For the QuickSIN test, the noise was also presented at 0 degrees azimuth. Speech stimuli across all conditions were presented at a fixed level of 75 dB SPL.

All participants first completed the SPIN tests in an unaided condition. Following baseline testing, participants were fit with Starkey Genesis AI RIC RT hearing aids. All fits were verified using real-ear measures with the NAL-NL2 fitting formula and were within 5 dB of target at all frequencies. Participants were then provided with the hearing aids to use in their daily life for 4 weeks. They were instructed by the research team how to manually activate “Edge Mode™” and were encouraged to use the devices during all waking hours. Datalogging was monitored weekly. If average daily use fell below four hours, participants returned to the lab for re-instruction and device reprogramming, and their trial was extended by 1 week. All participants met this requirement without exception. After completing the 4-week field trial, participants returned to the lab and repeated the SPIN measures in an aided condition. In the post-fitting SPIN measures, each test was repeated twice, once with Edge Mode™ active, and once with it deactivated (i.e., using default “Personal” program).

To determine the subjective benefits of the Edge Mode™ algorithm, we examined participant preferences during the take-home field testing period. During this four-week timeframe, participants were required to wear the devices for at least 4 h each day in the default Personal program, and to use the on-demand Edge Mode™ program at least twice daily. Subsequently, subjects answered a total of six questions (Appendix 1) regarding their subjective preference for the Personal program or Edge Mode™ via survey or ecological momentary assessment questionnaire through a smartphone mobile application. This allowed assessment of subject participants’ overall preference, ease of use, and the perceived listening environment when either the personal program or Edge Mode™ was used. Subjects were blinded to the use of EMA “catch” trials (randomized to 30%) that used an audible indicator but did not apply acoustic changes when the on-demand feature was activated.

Statistical analysis

Our primary objective in this phase was to assess the influence of a speech enhancement algorithm on improving speech understanding abilities in noise. For each SPIN measure, we compared performance with the algorithm active vs. inactive via

a paired *t*-test. We then examined the relationship between the magnitude of improvement (if any) and the degree of hearing loss by completing a linear regression on the difference between active and inactive modes vs. the degree of hearing loss as determined by the High-Frequency Pure Tone Average (HFPTA; average at 1, 2, and 4 kHz). Finally, we examined the relationship between the magnitude of improvement (if any) on a given SPIN test when the algorithm was active relative to the pre-fitting unaided performance on that test.

For the subjective ratings obtained in Phase II, we calculated the percentage of improvement, no change, or worsening of speech understanding after turning on the Edge Mode™, and the percentage of preference for Edge Mode™ or automatic mode, stratified by environment or noise level. We used a one-sample binomial test to determine (1) whether the observed proportion of improvement is statistically significant compared to the random 50–50% chance; (2) whether the observed proportion of improvement is significantly different from that of worsening when Edge Mode™ was turned on, in each environment and at each noise level and all scenarios combined. The same test was used to test the preference for Edge Mode™ or automatic mode. *P*-values < 0.05 was deemed to be statistically significant under two-tailed test.

Results

Phase I

Results from Hagerman and SII computations indicate that in comparison to baseline amplification conditions with omnidirectional microphones and no noise reduction, the default Personal program provided an SNR improvement of over 7 dB in challenging listening environments (e.g., “bar” or “construction” environments), and up to 13 dB SNR improvement (vs. the base condition) when Edge Mode™ was enabled (Figure 4). The magnitude of benefit varied across the seven “real-life” conditions, but each showed predicted SPIN and SNR improvements for the Edge Mode™ conditions over the default Personal program conditions. Additionally, the magnitude of benefit will vary with acoustic coupling used (e.g., occluded vs. vented domes or earmolds) under “real world” conditions.

Phase II: behavioral SPIN performance

Taken together, our results show improvements with activation of the signal processing algorithm on the CNC +5 SNR, the QuickSIN and the WIN, but not on the NST +5 SNR. In all instances, these improvements were independent both degree of hearing loss and the unaided pre-fitting performance. Figure 5 shows group performance on the CNC+5 condition when the algorithm was active or inactive (left panel), while individual improvements are depicted in the right panel. Here a significant improvement in performance was observed when the algorithm was active ($t_{20} = 5.30$, $p < 0.001$). A moderate relationship was observed with performance when the algorithm was on and off ($p = 0.007$; $R^2 = 0.46$), with the slope

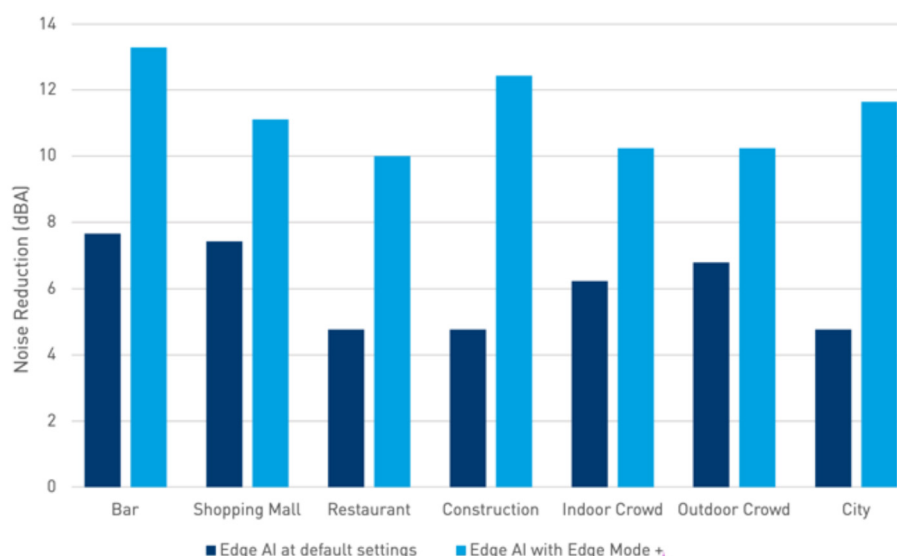


FIGURE 4

SII-weighted SNR improvement with a variety of challenging diffuse noise environments with Edge Mode™ hearing aids. The bars show comparison between the automatic default Personal program (dark blue) and Edge Mode™ (light blue), vs. the baseline condition of omnidirectional microphone and noise reduction disabled.

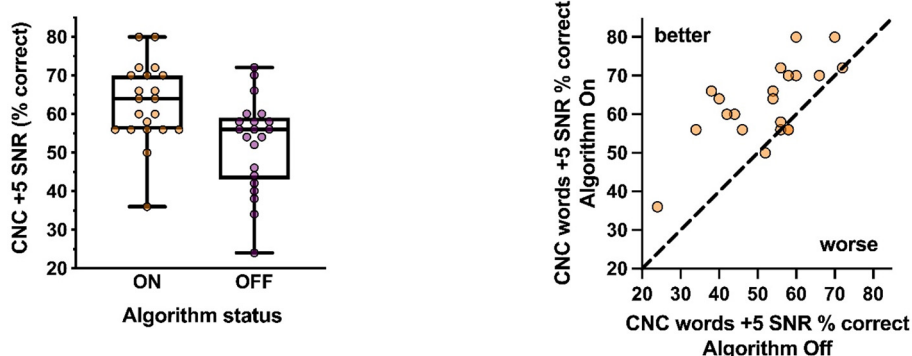


FIGURE 5

Group performance in the CNC+5 condition with the algorithm active or inactive (Left) and individual improvements (Right). Significant improvement was observed with the algorithm active.

of the line suggesting that greater improvements were more likely to be observed when performance without the algorithm was lower. Finally, the magnitude of these improvements was unrelated to both the degree of hearing loss ($p = 0.33$; $R^2 = 0.05$) and the unaided performance ($p = 0.69$; $R^2 = 0.01$).

Similar results were observed for the QuickSIN (Figure 6). Small, but statistically significant improvements were observed on the QuickSIN when the algorithm was active vs. not ($t_{20} = 3.59$, $p = 0.002$). A strong relationship was observed between the algorithm on vs. off conditions ($p < 0.001$; $R^2 = 0.87$), with the slope of the line suggesting that the magnitude of improvement was similar regardless of the performance without the algorithm. As with the CNC+5 SNR, these improvements

were not related to the degree of hearing loss ($p = 0.93$; $R^2 = 0.001$) nor the unaided QuickSIN performance ($p = 0.2$; $R^2 = 0.09$).

As with the QuickSIN, small, but statistically significant improvements were observed with the WIN (Figure 7) when the algorithm was active relative to when it was not ($t_{20} = 2.12$, $p = 0.046$). A strong relationship was again observed between the algorithm on and off conditions ($p < 0.001$; $R^2 = 0.73$), with the slope of the line suggesting that, when improvements are observed, their magnitude was similar regardless of the performance without the algorithm. Any improvements were once again unrelated to the degree of hearing loss ($p = 0.48$; $R^2 = 0.03$), and the unaided performance ($p = 0.45$; $R^2 = 0.03$).

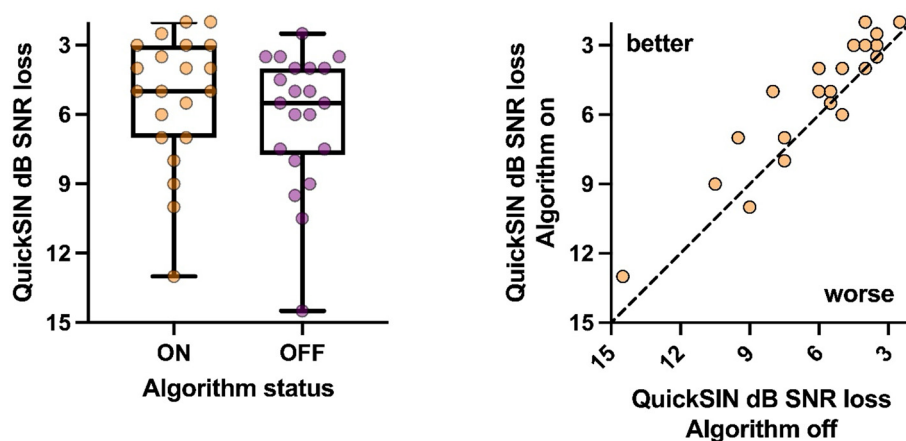


FIGURE 6

Group (Left) and individual (Right) performance on QuickSIN with the algorithm active and inactive were significant.

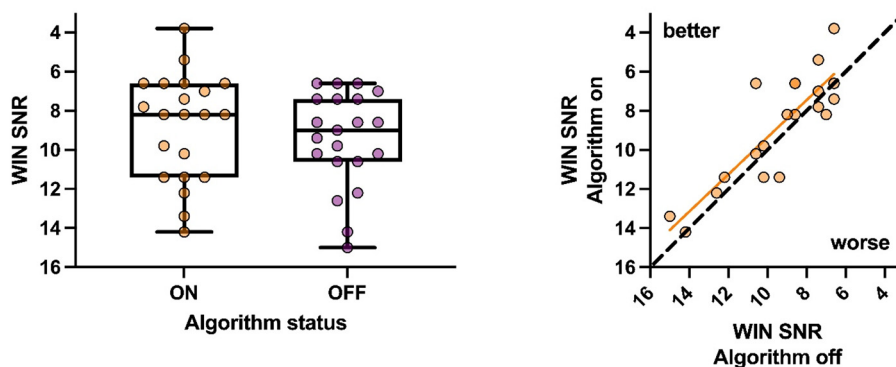


FIGURE 7

Group (Left) and individual (Right) performance on WIN with the algorithm active and inactive were significant.

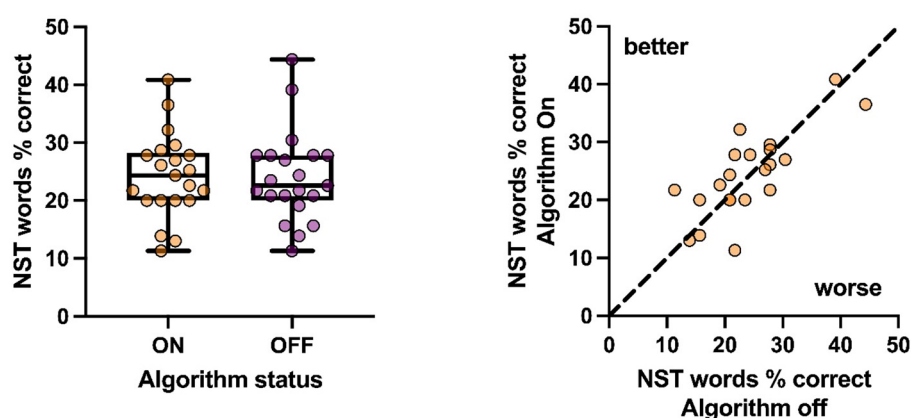


FIGURE 8

Group (Left) and individual (Right) performance on NST words with active and inactive algorithm were not significant.

Unlike the previous SPIN tests, there were no differences observed on the NST+5 SNR (Figure 8) when the algorithm was active or inactive regardless of whether the test was scored as

whole words ($t_{20} = 0.26$, $p = 0.81$) or phonemes ($t_{20} = 0.82$, $p = 0.42$). A significant relationship between NST performance with the algorithm on and off was observed ($p < 0.001$; $R^2 =$

0.59), consistent with the idea that better or worse performance without the algorithm is unchanged when the algorithm is active. Finally, no relationship was found between the magnitude of improvement (if any) and the degree of hearing loss ($p = 0.79$; $R^2 = 0.003$), or the unaided performance on the NST ($p = 0.72$; $R^2 = 0.007$).

Phase II: subjective ratings

The primary objective in this phase was to assess whether the measured laboratory benefits from Phase I and clinical benefits in Phase II were perceived as beneficial by participants during take-home testing using EMA and subjective testing. Here, significant improvements when Edge Mode™ was active were reported across all listening environments (Figure 9). Even after accounting for the catch trials, participants reported significant improvements ($p < 0.001$) for the questions asking about improvements in speech understanding and reduction in listening effort. Finally, when asked about listening preference between Edge Mode™ and the Personal program (Figure 10), participants were more likely to prefer listening with the Edge Mode™ active ($p < 0.001$) when in noisy environments.

Discussion

In this multiphase assessment of a DNN-based on-demand hearing aid feature (Edge Mode™), we demonstrated strong support in Phase I for the theoretical benefits in laboratory conditions using the Hagerman method and via predicted audibility represented by SII computations. In Phase II we also observed significant improvements in both lab-based measures of speech perception in noise, and subjective benefit in real-world environments as measured by EMA questionnaires. However, these benefits were observed on some tests (CNC + 5 SNR, QuickSIN and WIN), but not others (NST + 5 SNR). When observed, these benefits were independent of the degree of hearing loss and unaided pre-fitting performance. Taken together, these results suggest that this algorithm results in small, but significant improvements in the SNR relative to current signal processing techniques, but that these benefits may vary between individuals and may not be present with all types of background noise.

One of the most striking results observed here is that the algorithm improved SPIN abilities for all tests except for the NST+5 SNR. The most likely reason for this result reflects the differences in noise types between the two tests. Here, the NST used a speech-shaped noise, while the other tests utilized multi-talker babble. By this logic, the algorithm was most likely trained on various types of multi-talker babble and was subsequently unable to generalize any improvements to the speech-shaped noise. If so, these data suggest that this algorithm needs to be further refined to optimize the SNR in different acoustic environments. An alternative, less likely information is that the NST+5 required additional cognitive resources for optimal performance than the other tests, and the additional cognitive load obscured any improvement in SNR elicited by the algorithm. Single-word or

phoneme tests are often thought to rely more heavily on auditory cues because of their lack of context than sentence-based tests. Thus, one might expect that a non-sense syllable test should require the participant to focus more on purely auditory cues. However, participants may have attempted to assign meaning to the non-sense word and confused it with similar-sounding real words. If so, it may be possible that this process required additional cognitive load which obscured any benefits in SNR brought about by the algorithm.

One implication of observing benefits for some SPIN tests but not others is that it suggests that the benefits observed here are not resulting solely from a directional microphone. If this were the case, then we should have observed improvements in all SPIN tests. However, the fact that the same speaker configuration was used for all tests, and that differences were only observed for the test which used speech-shaped noise instead of multi-talker babble, suggests that other factors in the signal processing algorithm than microphone directionality accounted for the small but significant improvements observed here.

While significant improvements were observed in three of the four SPIN tests used here, it is worth noting that the improvements were on average relatively small on average (~1 dB for the QuickSIN and WIN, and 10% for the CNC+5), and often varied between individuals. For example, the smallest effect size was observed for the WIN (Cohen's $d = 0.42$, indicating a small effect), while the effect sizes were larger for the QuickSIN and CNC+5 (0.78 and 1.16, respectively). One possibility is that the smaller effect size with the WIN reflects the test administration. In this test, the noise level is fixed, and the level of the signal is systematically reduced. In contrast, the signal level is fixed with the QuickSIN and the CNC+5 tests, and the noise level is varied in the QuickSIN. One implication of this difference is that for some participants, there may have been a reduction of audibility for some signals, which could have hindered the effectiveness of the algorithm. Such confounds are less likely with the QuickSIN or the CNC+5 as the speech level and thus audibility was fixed in these measures, and this may help account for the reduced effect size for the WIN.

Another possibility is that the between-participant variability observed here regarding the effectiveness of the algorithm reflects individual differences between participants regarding distortions of peripheral encoding or executive function. For example, when measured in thousands of patients, performance on the QuickSIN and WIN has been shown to vary considerably between individuals with similar amounts of hearing loss (Fitzgerald et al., 2023; Wilson, 2011; Smith et al., 2024). In some instances, these between-subject differences are often attributed to differences in peripheral encoding of the signal. These include, and are not limited to, deficits in spectral-temporal modulation (Bernstein et al., 2013; Mehraei et al., 2014; Bernstein et al., 2016), temporal fine structure (Moore et al., 2008; Lorenzi et al., 2006; Hopkins et al., 2008; Viswanathan et al., 2021), the encoding of the fundamental frequency (Coffey et al., 2017; Mepani et al., 2021), synaptopathy (Liberman et al., 2016; DiNino et al., 2022), and the distortion of tonotopicity (Parida and Heinz, 2022a,b). In other instances, differences in executive function capacity have been put forth as predictors of SPIN abilities. For example, reducing working memory capacity is consistently associated with poor performance on SPIN measures in elderly patients (Humes, 2021b; Akeroyd, 2008; Janse and

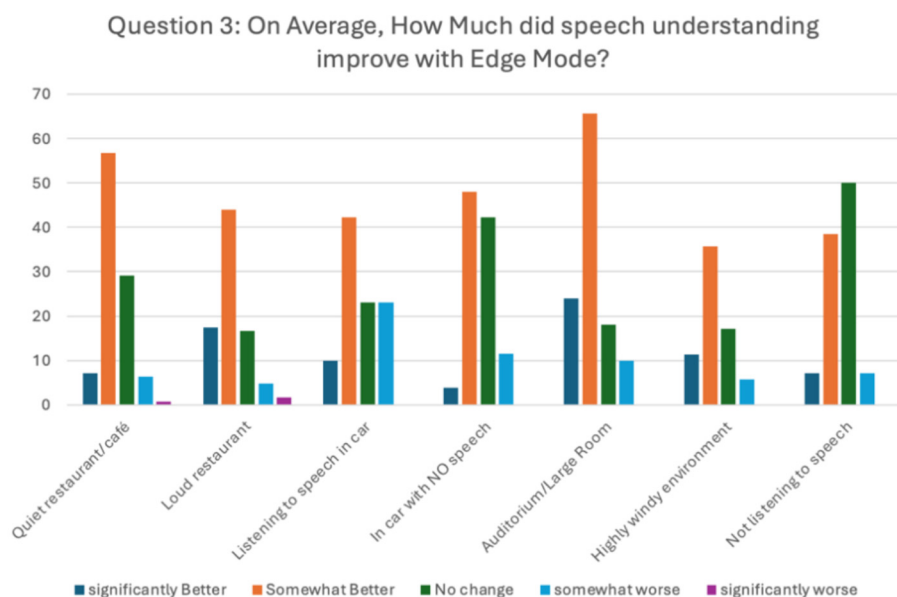


FIGURE 9

Subjective results from take-home testing comparing preference for the default Personal program vs. Edge Mode™ for seven quiet and noisy listening environments.

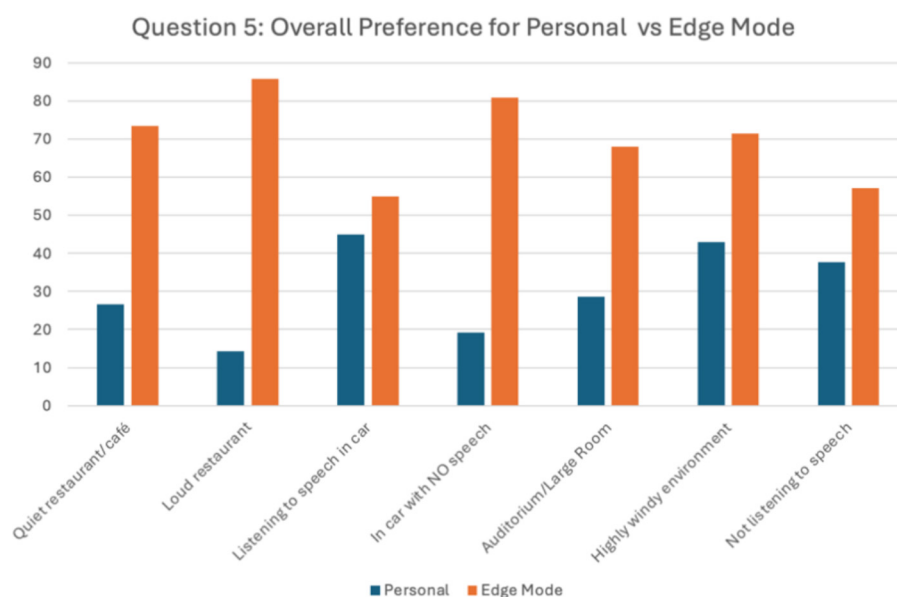


FIGURE 10

Overall preference for Personal vs. Edge Mode™ programs reported from take-home testing for seven quiet and noisy listening environments.

Jesse, 2014; Souza and Arehart, 2015; Nagaraj, 2017; Vermeire et al., 2019; Yeend et al., 2019; Humes, 2020). Other aspects of executive function, such as cognitive flexibility, are also associated with SPIN abilities in adults (Rosemann and Thiel, 2020; Helfer et al., 2020). Regarding the present data, it is possible that the algorithm used here may facilitate improvements in the SNR for some types of deficits in peripheral encoding or executive function, but not others. For example, some older adults may be more

sensitive to distortions of the speech signal caused by some types of hearing aid signal processing (Arehart et al., 2013), and that these differences can be mediated or influenced by spectral distortion of between-subject variance in executive function capacity (Davies-Venn and Souza, 2014; Souza et al., 2015; Rallapalli et al., 2021; Windle et al., 2023; Rallapalli et al., 2024). By this logic, the algorithm used here may be more effective for some individuals than others, but the pre-test and fitting procedures used here

were insufficient to predict which individuals would be most likely to benefit.

Another key result from this study is that, when improvements were observed on behavioral SPIN abilities, they were not related to the degree of hearing loss, or the unaided performance on any of the SPIN measures tested here. The most likely interpretation of these results is that the signal-processing algorithm used here results in enhancement of speech features for all signals, and that participant-specific factors (e.g., differences in peripheral encoding or executive-function abilities) determined the extent to which they could make use of the enhancements elicited by the algorithm. Such data speaks to the need for improved-prefitting measures to allow for greater precision in fitting of hearing aids beyond maximizing audibility according to pre-specified formulae such as NAL or DSL.

In addition to the behavioral improvements in SPIN performance observed with the Edge Mode™ algorithm, these participants also reported significant subjective improvements when the algorithm was active. These preferences were observed in both quiet and noisy listening environments, and were almost uniformly in favor of the Edge Mode™ algorithm. This subjective preference is consistent with a recent report indicating that improved SPIN performance was associated with a reduction in perceived auditory disability in a large cohort of more than 1600 patients (Fitzgerald et al., 2024). Moreover, SPIN abilities correlate with hearing aid satisfaction (Saunders and Forsline, 2006; Davidson et al., 2021; Walden and Walden, 2004), such that patients with better SPIN abilities are happier with their devices. Conversely, SPIN abilities are often worse in patients who return their hearing aids (Humes, 2021a), and difficulties with SPIN are commonly reported to be responsible for inconsistent hearing aid use, or discontinuing use altogether (McCormack and Fortnum, 2013; Hong et al., 2014; Humes, 2003; Hickson et al., 2014; Jilla et al., 2020; Powers and Rogin, 2020; Aazh et al., 2015). Taken together, these data suggest that even relatively small improvements in SNR over conventional signal processing can be noted by patients and result in improved preference. Thus, these data suggest that the future potential for DNN-assisted noise management has significant potential to further improve the communication abilities of individuals with hearing difficulties.

Conclusions

Here we evaluated the efficacy of a DNN-based hearing aid signal processing algorithm in improving speech perception in noise (SPIN) in 20 participants with hearing loss, in addition to objective evaluations in a laboratory setting. We observed significant improvement in SPIN abilities on the CNC+5 SNR, QuickSIN, and WIN tests but not on the NST+5 SNR. We speculate that the lack of improvement on the NST+5 SNR is likely due to its use of speech-shaped noise, unlike the multi-talker babble in other tests. This suggests that the algorithm may have been optimized for speech understanding in the presence of competing talkers and would need to be refined for other listening conditions. The benefits observed here were somewhat variable between individuals and were independent of the degree of hearing loss unaided SPIN abilities. These

results likely reflect between-participant differences in as peripheral encoding and executive function which influence the ability of individuals to benefit from the signal processing used here. Finally, these SPIN improvements were reflected in the subjective preferences of these participants when using devices in their daily lives. Taken together, they suggest that artificial intelligence driven algorithms can elicit significant improvements in SNR in hearing aids, and that more precise tools are needed to improve pre-fitting measures to better tailor hearing aids to individual users.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

The studies involving humans were approved by Stanford University, Institutional Review Board. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

MF: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. VA: Formal analysis, Visualization, Writing – review & editing. MS: Project administration, Resources, Software, Writing – review & editing. JR: Data curation, Investigation, Project administration, Visualization, Writing – review & editing. SV: Data curation, Formal analysis, Investigation, Methodology, Visualization, Writing – review & editing. AB: Conceptualization, Funding acquisition, Project administration, Resources, Supervision, Writing – review & editing. RJ: Funding acquisition, Investigation, Resources, Supervision, Writing – review & editing. KS: Funding acquisition, Investigation, Project administration, Resources, Supervision, Writing – review & editing. DF: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Writing – original draft.

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Conflict of interest

MS, AB, and DF were employed by Starkey Hearing Technologies.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/fauot.2025.1677482/full#supplementary-material>

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