Preliminary Evaluation of Automated Speech Recognition Apps for the Hearing Impaired and Deaf

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12

13 **ABSTRACT**

14 **Objective.** Automated speech recognition (ASR) systems have become increasingly sophisticated,
15 accurate, and deployable on many digital devices, including on a smartphone. This pilot study aims
16 to examine the speech recognition performance of ASR apps using audiological speech tests. In
17 addition, we compare ASR speech recognition performance to normal hearing and hearing impaired

listeners and evaluate if standard clinical audiological tests are a meaningful and quick measure of the performance of ASR apps.

Methods. Four apps have been tested on a smartphone, respectively AVA (iOS, Android), Earfy (iOS, Android), Live Transcribe (Android) and Speechy (iOS). The Dutch audiological speech tests performed were speech audiometry in quiet (Dutch CNC-test), Digits-in-Noise (DIN)-test with steady-state speech-shaped noise, sentences in quiet and in averaged long-term speech-shaped spectrum noise (Plomp-test). For comparison, the apps' ability to transcribe a spoken dialogue (Dutch and English) was tested.

Results. All apps scored at least 50% phonemes correct on the Dutch CNC-test for a conversational speech intensity level (65 dB SPL) and achieved 90-100% phoneme recognition at higher intensity levels. On the DIN-test, AVA (iOS, Android) and Live Transcribe (Android) had the lowest (best) signal-to-noise ratio +8 dB. The lowest signal-to-noise measured with the Plomp-test was +8 to 9 dB for Earfy (Android) and Live Transcribe (Android). Overall, the word error rate for the dialogue in English (19-34%) was lower (better) than for the Dutch dialogue (25-66%).

Conclusion. The performance of the apps was limited on audiological tests that provide little linguistic context or use low signal to noise levels. For Dutch audiological speech tests in quiet, ASR apps performed similarly to a person with a moderate hearing loss. In noise, the ASR apps performed more poorly than most profoundly deaf people using a hearing aid or cochlear implant. Adding new performance metrics including the semantic difference as a function of SNR and reverberation time could help to monitor and further improve ASR performance.

1 INTRODUCTION

40 Automated Speech Recognition (ASR) has become increasingly sophisticated and accurate as a result
41 of advances in deep learning, cloud computing, and the availability of large training sets (1,2). The
42 software converts speech into text using artificial intelligence models that have been trained on vast
43 collections of speech containing millions of words. ASR software is widely available on most digital
44 devices, including smartphones, tablets, or laptops. It is primarily used for voice commands (e.g. hey
45 Siri!), at the workplace to create transcripts, or in class for taking notes. Recently, ASR has become
46 available in online meetings (e.g. Microsoft teams) and video recordings (e.g. Google's Youtube) to
47 provide automatic captions. Also, several ASR-based speech-to-text apps have been developed for
48 the hearing impaired and deaf, providing live captioning of conversations (2,3), showing the potential
49 of automation and artificial intelligence for hearing healthcare (4,5). Early in 2020, we were
50 confronted in our clinic with questions from patients related to the use of ASR apps for daily
51 communication. These questions were especially common among patients with severe to profound
52 hearing loss who visited our outpatient clinic to assess if they were eligible for a Cochlear Implant.
53 Also, patients who had experienced sudden deafness, but had not yet been fitted with hearing aids,
54 made use of an ASR app during their appointments. There was no or little experimental information
55 at the time about the performance and usability of the ASR apps for hearing impaired persons beyond
56 what was shared by developers. Nor did we have clear criteria for which groups of patients we might
57 suggest the ASR apps to.

58 Since 2017, several ASR systems have claimed speech recognition performance close to that of
59 normally hearing humans (1,2). The most common metric to express ASR performance, used to
60 underpin these claims, is the word error rate (WER). WER is calculated by adding the number of
61 missing, wrong, and inserted words and dividing this by the total number of words (6). A lower WER
62 score means better performance. The performance of ASR will be best for speech similar to the
63 speech on which it was trained (7). It is therefore important to understand for what specific task an
64 ASR is designed for and how it is evaluated. Typically ASRs are evaluated on well-studied large

(>100 hours) collections of speech, referred to as a corpus. The SwitchBoard corpus and CallHome corpus are well-known collections of conversational phone calls (8), whereas Librispeech is a corpus comprising speech from public domain audiobooks. The SwitchBoard corpus consists of conversations over the phone between strangers about a given topic (9). The CallHome corpus consists of more informal conversations between friends and family (8). None of these corpora are ideal for use in acoustically challenging environments. The SwitchBoard and CallHome were collected under low noise and low reverberation conditions (9), and a large portion of the Librispeech corpus has undergone noise removal and volume normalization (10).

In order to obtain estimates of human speech recognition performance that could be used for comparison with ASR, some researchers have determined the WER among professional transcribers of speech from the SwitchBoard and CallHome corpora. Saon et al. (2017) estimated the lowest (best) achievable WER, 5.1% for SwitchBoard and 6.8% for CallHome, based on the best score taken from three professional speech transcribers after a quality check by a fourth speech transcriber (1). Xiong et al. (2017) on the other hand, followed more realistic industry standard procedures, which are similar to how speech is processed by ASR (2). The reported WERs were 5.9% for SwitchBoard, and 11.3% for CallHome.

For some commonly-used systems ASR systems, WERs of 5.1% (Microsoft) and 5.5% (IBM) have been reported using the SwitchBoard corpus (11), which is close to the performance of normal hearing professionals reported above (1,2). Benchmark results of widely used ASR systems tested on the same corpora are not available to our knowledge. Google reported a WER of 4.9%, but used a non-public corpus (11). Koenecke et al. (2020) compared the performance of ASR systems from Amazon, Apple, Google, IBM, and Microsoft to transcribe structured interviews using two recent developed corpora (CORAAL and AAVE; (7)). However, transcribing a structured interview is a very different task than transcribing a conversation in real-time in acoustically challenging environments. More ecologically valid tasks are needed that take account the effects of noise,

90 reverberation, talker accent, and slang, for instance, to provide a realistic estimate of ASR
91 performance when used for conversations in daily life under various acoustic conditions.
92 For people with hearing impairments, there are specific user needs to consider when developing ASR
93 apps. For example, these listeners might use both speechreading (12) and text reading of the ASR
94 transcript from a screen. Speechreading conveys important nonverbal cues and nuances not included
95 in a transcript and may enhance speech-in-noise abilities (13). However, without careful design,
96 reading a transcript may interfere with someone's speechreading ability. Speaker identification cues
97 (e.g by color coding each speaker a feature in AVA (14)) may also direct the reader to the face of an
98 active talker. Other design ideas include the notification of critical environmental sounds (a feature
99 incorporated in Live Transcribe (15)), feedback to the speaker of their intelligibility of the ASR, or
100 feedback to the speaker by making the transcript readable from two sides (e.g mirrored) so that both
101 the speaker and the listener can check the results (incorporated in Earfy (16)).
102 The settings where an ASR is used may also differ between individuals with impaired or normal
103 hearing. For example, the settings where people with hearing loss use ASR may be more often in a
104 more homely atmosphere between family members that might use more colloquial language or slang.
105 That situation may be similar to closed caption for video series. The most common complaint of
106 people with hearing loss is the reduced speech perception in complex listening environments
107 including cocktail parties, restaurants, in conversations with their doctor, and family gatherings
108 (15,16). Adverse acoustic conditions, including low signal-to-noise, make it difficult for normal
109 hearing listeners to understand speech and make the speech incomprehensible for persons with mild
110 to profound hearing loss. Finally, the speed of translation to accommodate a fluent conversation and
111 the user interface to make it practical for older users and digitally less proficient users are factors to
112 consider.
113 A standardized task that fully captures the skills of humans to recognize speech does not yet exist, to
114 our knowledge. Such a task would need to account for factors as background noise, reverberation,

115 accent, and speech impairment. This is needed to verify claims that ASR speech recognition
 116 performance is close to humans (1,2) and should be done using diverse training datasets (7).
 117 This pilot study aimed to examine the speech recognition performance of ASR apps using
 118 audiological speech tests. We normally administer clinical audiology tests in patients from normal
 119 hearing to profound hearing loss to assess speech recognition. We tested the hypothesis that our
 120 clinical tests might thus provide objective metrics for performance of ASR systems for people with
 121 hearing loss, helping us to determine what range of hearing losses could benefit from ASR apps. In
 122 addition, we compared ASR results to normal hearing and hearing impaired listeners and evaluated if
 123 standard clinical audiological tests provide a meaningful and quick measure of the performance of
 124 ASR apps.

125

126 **2 METHODS**

127 Four different apps on two smartphones, with various operating systems, were tested on their ability
 128 to transcribe speech. For this project, the iOS operating apps were tested using an iPhone 6, and for
 129 the Android operating apps, a Samsung A3 was used. Both smartphone devices are widely used. We
 130 decided to select inexpensive ASR apps (<\$10) since they would be most widely used by our patients
 131 while the cost for ASR apps is not reimbursed in the Netherlands. The four apps tested were Ava and
 132 Earfy that both run on iOS and Android, Speechy iOS only, and Live Transcribe Android only. The
 133 tested apps were chosen by searching on the Internet on November 18th, 2019, for the best-known
 134 speech recognition apps for the hearing impaired and deaf as well as good reviews on the different
 135 app-stores. Also, the apps needed to be suitable to convert English and Dutch speech into text and
 136 inexpensive (less than \$10 for a license).

137

The apps were evaluated in similar test conditions used to assess speech reception in human listeners in Dutch Audiology Centers according to best local clinical practice. The smartphones were placed one meter in front of a speaker in a sound treated room compliant with ISO 8253-1 (19). Standard clinical calibration protocols were used for all speech material. The microphone of the smartphone was aimed towards the speaker, which we assumed to be the optimal microphone orientation, at approximately the height of a listeners' ears to resemble testing conditions when tested with human listeners. The smartphone screen was facing upwards allowing the experimenter to read the text from the screen. Four different speech reception tests were performed to evaluate the apps' ability to convert speech into text.

--- insert figure 1 around here ---

First, the apps were tested on speech recognition in quiet by converting a list of single words into text. The standard Dutch speech recognition test for this purpose was the Dutch CNC-test, which consists of phonetically balanced lists of twelve monosyllabic Dutch words in quiet (CNC-list, 'Nederlandse Vereniging voor Audiologie'; (20)). The words were played through a speaker, scored and displayed in a phoneme recognition score. All words consisted of three phonemes with a consonant-nucleus-consonant (CNC) structure. The first word was a test word and was not included in the scoring. A human observer performed the scoring by reading the word from the screen and counting the number of correct phonemes. Inserted phonemes were subtracted from the score according to the clinical scoring procedure (20). If a displayed word changed during the test, the final word was scored. A 100% phoneme recognition score was reached if all 33 phonemes of the 11 words were correct. Several lists were presented at an intensity level of 45, 55, 65, 75, and 85 dB sound pressure level (SPL) and the speech recognition as a function of presentation level (known in

human listeners as speech audiogram) is plotted for each app. For comparison, normal hearing listeners achieve 100% phoneme recognition at 45 dB SPL (20).

Second, the Plomp-test (Dutch sentences in noise) was presented (21). The test consists of 13 sentences of 8 to 9 syllables presented in noise with the same averaged long-term spectrum as the speech. A sentence was scored to be either correct, if the whole sentence was correctly presented on the screen, or incorrect, which was according to the conventional scoring procedure in clinical practice (22). The speech recognition threshold (SRT) in noise was defined as the signal-to-noise ratio (SNR) expressed in dB where on average 50% of the time the sentences were transcribed correctly, following the adaptive procedure described by Plomp and Mimpen (1979; 20). The test was first performed without the noise to obtain the SRT in quiet. Afterward, the masking noise level was set 15-20 dB above the SRT of the apps in the quiet situation, which was 70 dB SPL for all apps, to determine the speech reception threshold (SRT) in noise.

Third, a DIN-test (Digits-in-Noise) was performed. Digit triplets (e.g. 1 2 5) were presented in a long-term average speech-spectrum noise via a 1-up, 1-down adaptive SNR procedure. SRT was expressed in dB SNR, where a listener can on average recognize 50% of the digit triplets correctly. A test series consisted of 24 triplets. The first four triples were not used to determine the test outcome. The noise level was set at a fixed level of 60 dB with an initial positive SNR of 6 dB. The stepsize to adjust the level of the triplets was 2 dB. The DIN-test has a measurement error in humans of 0.7 dB (23).

Finally, a fragment of dialogue in Dutch and English at 72.2 dB(A) was presented through the speaker to recreate a more realistic listening setting. The Dutch dialogue was an introduction video of the Radboudumc with a female voice, talking clearly and at a normal pace

(<https://www.youtube.com/watch?v=zBJBD1-ePRw>). For the English dialogue, part of an advanced English tutorial was played. In this video, a conversation could be heard between a male and female voice (<https://www.youtube.com/watch?v=JtMgw2rCYSo&t=1s>). The Dutch dialogue consisted of 256 words, while the English dialogue consisted of 248 words. After the whole dialogue was played, scoring was performed on the transcript outputted by the app. The number of missing, wrong, and inserted words was counted and expressed in the WER.

In the end, a test-retest was performed to provide insight into the accuracy of the apps. All apps were retested on the CNC-test. The test-retest reliability on the CNC-test was visually assessed using a Bland-Altman graph. The best scoring app on the DIN- and Plomp-test, one for iOS and one for Android, was retested for both speech-in-noise tests. The root mean square difference (RMSD) was calculated for these results. No retest was performed for the dialogue.

3 RESULTS

The results for all apps on the Dutch CNC-test (words in quiet) are shown in Figure 2. The Speech Recognition as a function of presentation level was determined per app by interpolating a line using logistic regression on all available-data points (test and retest measurements). A 100% phoneme recognition was reached around 80 dB SPL for all apps except Earfy. Earfy (iOS and Android) scored 90% words correctly around 90 dB SPL. The shape of the apps' "speech audiogram" curves look similar to the s-shaped psychometric curve of normal hearing listeners determined by Bronkhorst et al. (1993) in 20 normal hearing university students (24). However, all apps' SRT were between 50 and 60 dB SPL, which is 25 to 35 dB poorer than normal hearing listeners who have a SRT around 25 dB SPL (20).

210

211 --- insert figure 2 around here ---

212

213 The speech-in-noise results are shown in Figures 3 and 4. All apps score a signal-to-noise ratio
 214 (SNR) higher than +8 dB on the DIN- and Plomp-test. Live transcribe (Android), and AVA
 215 (Android, iOS) achieved the best results on the DIN-test. Earfy on Android performed better than on
 216 iOS. Live Transcribe (Android) and AVA (iOS) achieved the best result using the Plomp-test. There
 217 was a notable difference between the operating systems for AVA and Earfy when measured with the
 218 Plomp-test.

219 --- insert figure 3 & 4 around here ---

220

221 In figure 5, the WER scores for both the Dutch and English dialogue are shown. Overall, the dialogue
 222 in English (WER 19-34%) was more correctly converted into words than the Dutch (WER 25-66%)
 223 dialogue. Speechy (iOS) had best matching result for English and Dutch (WER of 19% and 20%).
 224 Earfy (iOS) showed the greatest difference between English and Dutch (WER of 19% and 66%).

225 --- insert figure 5 around here ---

226 The test-retest reliability of the CNC-test can be seen in figure 6. Visual inspection of the Bland-
 227 Altman plot for the CNC-test-test did not show signs of any systematic bias in the relationships
 228 between differences and averages. The test-retest comparison of the CNC-test showed three outliers.
 229 Earfy for iOS exhibited large differences between the measurements at 70 and 90 dB and Live
 230 transcribe (Android) had a large difference between measurements at 50 dB. The test-retest reliability
 231 on the DIN- and Plomp-tests was assessed for one Android and one iOS app. The test-retest
 232 difference expressed in Root-Mean-Square-Difference on the DIN-test was 0.4 dB iOS Ava and 0.8

233 dB Android Live Transcribe, which we regard as acceptable since in normal hearing listeners tested
234 monaurally using headphones, 90% of measurements are within 1.4 dB (measurement error is 0.70
235 dB) for a single list on the DIN-test (23). The Root-Mean-Square-Difference on the Plomp-test was
236 0.6 dB iOS Ava and 2.0 dB for Android Live Transcribe.

237 --- insert figure 6 around here ---

238

239 4 DISCUSSION

240 Main results

241 None of the ASR apps achieved performance close to normal hearing listeners on audiological tests.
242 In quiet, ASR apps performed similarly to listeners with a moderate hearing loss. When transcribing
243 speech-in-noise, the ASR apps performed in the performance range of CI recipients. Sentences-in-
244 noise provided a quick test to assess ASR performance since that test material provided more
245 linguistic cues than digits-in-noise or lists of CNC words.

246 Performance compared to human listeners

247 The performance of the ASR apps on speech-in-quiet tests seems comparable to listeners with a
248 moderate conductive hearing loss (30-35 dB threshold shift), which is known as disabling for certain
249 activities in daily life (25). In comparison, Dingemanse & Goedegebure (2019) found a mean score
250 of 82% in 50 adult unilateral CI-recipients on the Dutch CNC-test tested in free field at 65 dB SPL,
251 which is the level of conversational speech (26). This performance may be an overestimation for the
252 average CI-users since they excluded participants with a CNC-score below 60%. Kaandorp et al.
253 (2015) determined a mean score in free field at 65 dB SPL of 95% while using their preferred device
254 in 24 hearing aid users with a moderate to severe hearing loss and 80% in 24 CI recipients (27). Only

255 for speech at high-intensity levels, well above the level of conversational speech, do the apps achieve
256 90 to 100% speech reception. The poor performance at low speech intensity levels may be caused by
257 hardware limitations, as discussed below in the section on hardware. The ASR may score lower due
258 to the lack of contextual information provided in the test. The CNC-test was developed as an auditory
259 test that requires little linguistic skill. The listener can only use the consonant-vowel-consonant
260 structure and the fact that the lists contain only familiar existing words. The alternative of using
261 nonsense words, or nonsense sentences, would probably further deteriorate ASR performance while
262 being a valid test for assessing auditory function with a lower effect of language skills by the subject
263 (28). Most ASR are trained on sentences of realistic conversations (8). The strength of (deep
264 learning) ASR is based on using contextual information from a natural language processing model
265 (29). That contextual information is not available in word testing.

266 The performance of the ASR apps on the Digits-in-Noise test was very limited compared to humans.
267 Normal hearing listeners achieve on the DIN-test monaurally using headphones an SNR of -8.8 dB
268 (23). CI recipients rated on the same criteria as normal hearing listeners, typically achieve DIN scores
269 ranging from $+3$ to -6 dB. For instance, Kaandorp et al. (2015) found an average SNR of $-1.8 (\pm 2.7)$
270 dB in a group of 18 adult unilateral CI recipients in free field test conditions (27). The ASR is at a
271 disadvantage because in the DIN-test, contextual information is lacking and the priors for the ASR
272 and human are not the same. When doing a digits-in-noise test, a human will only report digits. For
273 the ASR it is not a 10-class problem but a problem with several thousand alternatives. The apps tend
274 to construct sentences rather than separate numbers. For conversations where it is important to catch
275 a number, such as the price of an item, the DIN-test might be a useful measure.

276 The performance of the ASR apps on sentences in noise (Plomp-test) was very limited and much
277 poorer than in people with a moderate hearing loss (21). Normal hearing listeners have an SRT at an
278 SNR of -8 to -10 dB (21), while the best ASR apps achieved $+8$ dB scores. Kaandorp et al. (2015)

279 found mean SRT on Dutch Sentences in noise by scoring keywords of +2.1 dB for 24 hearing aid
280 users (tested on their preferred ear) with moderate to severe hearing loss and +8.0 dB for 24
281 unilateral CI recipients (27). In CI-recipients, evaluation of speech-in-noise is often performed
282 scoring keywords, instead of full sentences as used in the original procedure by Plomp and Mimpen
283 (1979; 20). In another study, Kaandorp et al (2016) found a significant difference of 1.0 dB in favor
284 of a keyword scoring procedure compared to scoring full sentences (30). However, this 1.0 dB
285 keyword effect does not account for the large difference between the app's performance and the
286 performance of hearing aid users in noise. On the Plomp-test, which provides more linguistic
287 information than the CNC- and DIN-test, the apps' performance is far below that of the majority of
288 hearing impaired listeners and similar to the range of outcomes in CI-recipients.

289 Sentences with and without noise (Plomp-test) could be considered as a performance metric for ASR
290 apps in difficult listening conditions. Possibly with more natural sentences to provide even more
291 linguistic cues. Testing through a loudspeaker has the advantage that it takes the effect of room
292 acoustics into account, making the test condition more realistic. Instead of a sound booth, a room
293 with more representative acoustics for daily situations (e.g the reverberation time of a classroom or
294 using babble noise instead of speech-shaped noise) would provide even more representative results.
295 The current scoring procedure of the Plomp-test, based on fully correct sentences, leads to very high
296 SNRs that may underestimate the practical value of ASR for hearing impaired persons. For instance,
297 if an ASR in a conversation under noisy conditions provides keywords, it may already benefit the
298 person with hearing impairment. One could easily adopt the Plomp-test by determining the WER
299 score on a fixed SNR level to simulate above example. Or alternatively, accept a higher number of
300 mistakes (compared to none) in the adaptive test by using keywords (30). Besides audiological test
301 outcomes, the systematically collected feedback by groups of users (e.g. a focus group) would be

302 very helpful to further improve the accessibility and usability of ASR apps for hearing impaired
303 listeners.

304 In longer dialogues, all tested apps provided a running English transcript with a WER around 19-
305 34%. This roughly corresponds to 60-80% correct word (~ 1 -WER) scores and this is in the same
306 range as for persons with profound hearing loss who use a cochlear implant (31) and better than
307 hearing aid users with a profound hearing loss (32). For these groups, the use of the ASR apps tested
308 here would likely provide benefits.

309 **Hardware and platform variability**

310 A possible explanation for the poor performance at low levels could be the smartphone's microphone
311 gain settings and limited dynamic range rendering soft sounds undetectable (33). We chose a
312 microphone orientation, directing it to the speaker that we assumed was optimal for the task.
313 However, we did not check the directionality of the built-in microphones. In actual use, the
314 microphone orientation could be suboptimal, for instance, if a listener positions the device such that
315 it enables better reading of the transcript from the screen. Also in group settings, the user will likely
316 put the device flat on a table and thus not always point the microphone to the speaker. We did not
317 investigate the effect of suboptimal microphone orientation. Another explanation for the level
318 dependence in quiet could be pre-processing. Most ASR systems usually normalize the input (34).
319 Potentially the ASR systems classify soft sounds as non-speech or not of interest.

320 In English, there is not much difference between the apps or between the operating platforms.
321 Therefore, we do not expect differences in the Dutch version to stem from hardware differences
322 between the smartphones (e.g., microphone sensitivity) but from the implementation of the Dutch
323 language in the specific app or the used training data. The difference between iOS and Android was
324 only visible in Dutch. In Dutch, Earfy (iOS) and Ava (iOS) score significantly poorer.

There was no consistent difference favoring either iOS or Android versions of the apps. Earfy performed better on Android, while AVA performed better on iOS. For prospective users, the performance of the app depends on language, and may depend on the platform.

Limitations

The administered tests did not include the effect of accents or speech impairments (e.g. deaf speech; (7,35)). The displayed transcripts changed during the dialogue, and the transcript was evaluated at the end of the dialogue instead of in real-time. When reading the transcript in real-time, the performance of the speech recognition apps might be better or worse due to the changing words in real-time to construct a logical sentence.

When measuring performance in noise, an adaptive SNR procedure was used. The effect of noise could be more extensively studied by evaluating ASR by determining the Word Recognition Score (the convention in the field of audiology) or the Word Error Rate (the convention in the field of ASR research) on several fixed SNR levels (e.g. -5, 0, +5 and +10 dB SNR) that correspond to realistic listening conditions for people using a hearing aid (36). For ecological valid measures, the effect of different fluctuating noise maskers should be considered (37,38). Babble-noise or traffic noise is much more realistic than (artificial) steady-state speech-shaped noise. In the end, the performance of the ASR must be robust enough that users will put their trust in these apps even in formal situations such as a conversation with their doctor or audiologist.

In this study, only (audiological) speech-to-text performance of the apps was measured. The usability, processing speed, effect on speechreading, and readability of the transcript were not evaluated. Other researchers looked into requirements for speed and user interface and concluded that those are important factors to improve usability (39). We expect that an increasing number of ASR

347 apps will adhere to accessibility guidelines to improve usability for the elderly and people with
348 disabilities as promoted by the Web Accessibility Initiative (40).

349 The number of apps tested in this study is limited. We did not perform a standardized procedures for
350 literature review (e.g. PRISMA) to find and include ASR apps for this pilot study. In English, more
351 apps may be available than in Dutch and we did not include expensive state-of-the-art (professional)
352 ASR systems.

353 Other factors to consider not included in this pilot study are the distance between speaker and
354 listener, especially in these times of social distancing and the effect of face masks on a speakers'
355 voice and intelligibility (41). Feedback about voice quality could help the speaker adopt a more
356 intelligible speaker style. The errors made by the ASR may be complementary or redundant to the
357 errors made by persons with hearing loss. We did not study the error patterns. A potential way to
358 determine the complementary effect of ASR could be to evaluate speech-recognition in noise using
359 an audiovisual presentation mode, instead of the audio-only mode that was used in this study, in three
360 distinct aided conditions. 1) participants with hearing loss aided with hearing aid or CI. 2)
361 participants with hearing loss aided with hearing aid or CI and using an ASR app, 3) performance by
362 the ASR app only. Studying the difference between these conditions reveals the added benefit and
363 may penalize ASR systems not designed for simultaneous speechreading and text reading.

364

365 **Metrics to evaluate personalized ASR performance**

366 Instead of the quick audiological tests we performed here, a more conventional and elaborate
367 evaluation method would be to record several hours of conversations with hearing impaired users
368 (including realistic lexicon and acoustics) via a smartphone while the screen is oriented such that the

369 user can read the transcript. Subsequently, one could create transcripts of the recordings by human
370 transcriptions as ground truth, pass the recordings through several ASR apps and determine a
371 performance rating based on WER and other automated metrics such as the semantic distance
372 between the ASR transcript and ground truth (42).

373 ASR may benefit from domain-specific evaluation tools and have domain-specific applications. For
374 instance, Miner et al. (2020) developed a metric based on symptom-focused language in
375 psychotherapy (43). A domain-specific, or even person-specific factor is that prelingually deaf people
376 often have a speech impairment, leading to lower comprehensibility both for normal hearing listeners
377 who are not accustomed to deaf speech and for ASR apps that are not specifically trained on deaf
378 speech. Fortunately, generic ASR models can be used as a pre-trained model that subsequently is
379 trained on a particular task including atypical speech, accents, or acoustic conditions without
380 incurring the cost of training a full model (44). Recently, researchers from Google started a project,
381 called Parrotron, to create personalized models which could better convert deaf speech than generic
382 ASR systems. WER dropped from 89.2% for the generic ASR to 32.7% for the finetuned ASR for a
383 single prelingually deaf subject (35). In addition, the Parrotron system can synthesize the speech of a
384 speech impaired person (i.e. voice conversion) to make the speech sound more natural and
385 comprehensible to the untrained ear.

386 Metrics as, for example, the WER (SNR, RT), or semantic difference (SNR, RT), as functions of
387 signal-to-noise ratio and reverberation time (RT) can provide more ecologically valid estimates of the
388 benefits ASR apps could provide in daily life. Representative SNR values could include -5, +10, +30
389 (quiet) dB SNR. For ecological valid measures, realistic fluctuating noise masker should be used
390 (37,38). Reverberation times typically encountered in daily life to consider are 0, 0.5, and 2.5
391 seconds, which corresponds to ideal, classroom (45), and church (46) room acoustics. Presenting the

392 ASR performance using the WER (SNR, RT) reduces the need to study the characteristic of the
393 corpus on which the ASR was trained and or evaluated.

394 **Future benefits for audiologists**

395 ASR apps can provide benefits in conversations between patients and their audiologists (47). In
396 addition, ASR technology, when further developed, can play a role in computational approaches to
397 audiology (4). For instance, if personalized ASR apps further develop so that atypical speech is better
398 captured, and if ASR achieves normal hearing performance on audiology tests it may provide another
399 use case: patients could perform self-testing (i.e. automated speech audiometry) by repeating the
400 speech they hear to an ASR system trained on their particular voice replacing or enhancing the task
401 of the professional in the audiology center (48). Manual calculation of complex evaluation metrics is
402 not suitable in clinical settings given the excessive time required and may lead to inter-rater
403 variability (49). Automated speech audiometry using algorithms to score performance can be a
404 valuable complement to automated pure-tone threshold audiometry (50). For example, Vinail et al
405 (2016) validated a semi-automatic speech procedure using customized word-lists, in part, provided
406 by the subject to include familiar words. The customized word-lists were recorded with the subject's
407 own voice to incorporate personalized acoustic and articulatory parameters. Speech recognition was
408 evaluated on the customized word-list using an algorithm to determine automatically the number of
409 correctly repeated phonemes. In addition, the use of ASR could open venues to improved
410 (automated) scoring methods in audiology tests. Ratnanather et al (2021) demonstrated how one can
411 automate the alignment of phonemes based on the minimum edit distance between the source speech
412 and the utterances of the subject in real time (51). Visualizing this alignment may provide insights to
413 clinicians about what phonological errors are made.

414 A factor of variability in rating procedures is that in many speech-in-noise tests, the test is made
 415 easier for CI recipients by only scoring correct keywords rather than full sentences (28,30). Although
 416 scoring keywords makes the test accessible to a larger population, it reduces the discriminative power
 417 between higher- and lower-educated native listeners (30). An ASR could facilitate an automated
 418 scoring procedure that differentiates between errors. For instance, using semantic difference between
 419 the ASR transcript and ground truth, errors that lead to semantically similar sentences are weighted
 420 favorably, leading to a better outcome measure in terms of how well hearing impaired persons can
 421 participate in a conversation under adverse circumstances.

422

423 **5 CONCLUSION**

424 None of the ASR apps achieved performance close to normal hearing listeners on audiological tests.
 425 No app stood out from the others on performance level. On audiological speech tests in quiet, ASR
 426 apps performed similarly to listeners with a moderate hearing loss. When transcribing speech-in-
 427 noise, the ASR apps performed in the performance range of CI recipients. Sentences-in-noise
 428 provided a quick test to assess ASR performance. Additional performance measures are needed to
 429 evaluate ASR apps. Besides the speech material also type of noise and the presentation mode audio-
 430 only versus audiovisual need to be considered. Adding new performance metrics including the
 431 semantic difference as a function of SNR and reverberation time can help to monitor and further
 432 improve ASR performance. Clinicians can use benchmarks based on such metrics to counsel
 433 prospective users and may benefit from automated procedures. Several hearing impaired listeners,
 434 especially CI recipients, report that they benefit from the apps in certain situations(47), which is in
 435 accordance with the results of converting a dialogue into text and may stem from complementary

error patterns of ASR not investigated here. Personalized ASR could increase the number of listeners enjoying the benefits of ASR.

438

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577

578 7 CONFLICT OF INTEREST

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

581 8 AUTHOR CONTRIBUTIONS

582 LP, JWW and PvH conceptualized the study. LP, PvH and DG collected the data. All authors
583 contributed to the data interpretation, reviewed the results, and edited the manuscript. LP and JWW
584 took the lead in drafting the manuscript.

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592 1 DATA AVAILABILITY STATEMENT

593 The datasets generated for this study can be requested by contacting the corresponding author.

594

595 Figure Legends

596

597 Figure 1: Set-up of the smartphone in front of the speaker.

598

599 Figure 2: Speech recognition as a function of presentation level (in human listeners known as speech
600 audiogram) of all ASR apps tested on an Android and iOS smartphone. The plotted lines are

601 interpolated using a logistic function through the measured test-retest data-points. Left side: results of
 602 the Android apps, right side: results of the iOS apps.

603
 604 Figure 3: Digit in Noise results expressed in SNR per app. A lower score is better. The error bars
 605 represent the standard deviation of the response of the app within a single list of triplets.

606

607

608 Figure 4: Sentences in noise results expressed in SNR per app. A lower score is better. The error bars
 609 represent the standard deviation of the response of the app within a single list of sentences.

610

611 Figure 5: Word error rate in percentage of the dialogue in English and Dutch for the different apps.

612

613

614 Figure 6: Bland-Altman plot to display the test-retest reliability of the CNC-test.