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Research Article

Automatic Speech Recognition Predicts Speech Intelligibility and Comprehension for Listeners With Simulated Age-Related Hearing Loss

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Purpose: The purpose of this article is to assess speech processing for listeners with simulated age-related hearing loss (ARHL) and to investigate whether the observed performance can be replicated using an automatic speech recognition (ASR) system. The long-term goal of this research is to develop a system that will assist audiologists/hearing-aid dispensers in the fine-tuning of hearing aids.
Method: Sixty young participants with normal hearing listened to speech materials mimicking the perceptual consequences of ARHL at different levels of severity. Two intelligibility tests (repetition of words and sentences) and 1 comprehension test (responding to oral commands by moving virtual objects) were administered. Several language models were developed and used by the ASR system in order to fit human performances.
Results: Strong significant positive correlations were observed between human and ASR scores, with coefficients up to .99. However, the spectral smearing used to simulate losses in frequency selectivity caused larger declines in ASR performance than in human performance.
Conclusion: Both intelligibility and comprehension scores for listeners with simulated ARHL are highly correlated with the performances of an ASR-based system. In the future, it needs to be determined if the ASR system is similarly successful in predicting speech processing in noise and by older people with ARHL.

Age-related hearing loss (ARHL)—the progressive decline with increasing age of hearing sensitivity, as measured by an audiometric assessment—affects more than 45% of the population over the age of 48 years (Cruickshanks et al., 1998). The most common complaint of listeners with ARHL is the difficulty to understand speech, especially in noisy environments (e.g., CHABA, 1988). In part, this difficulty results directly from the loss in audibility of the speech signal, but it is also due to additional deficits in suprathreshold auditory processing, such as loudness recruitment, loss in frequency selectivity (e.g., Nejime & Moore, 1997), and reduced sensitivity to temporal–fine structure and temporal-envelope information (e.g., Füllgrabe, 2013; Füllgrabe, Moore, & Stone, 2015). When left uncorrected, speech-perception difficulties can compromise interindividual communication, resulting in various negative consequences for the affected person, such as social isolation (e.g., Strawbridge, Wallhagen, Shema, & Kaplan, 2000), depression (e.g., Gopinath et al., 2009), and accelerated cognitive decline (e.g., Lin et al., 2013).

Currently, the standard treatment for ARHL is digital hearing aids (HAs), providing amplification in a number of frequency channels in order to restore the audibility of sounds. However, up to 40% of the listeners fitted with HAs never or rarely use their devices (Knudsen, Öberg, Nielsen, Naylor, & Kramer, 2010). One explanation for this high rejection rate might be the quality of HA fitting, resulting in suboptimal speech-intelligibility benefits.

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Traditionally, speech perception is measured by determining the percentage of speech items (e.g., words) that are correctly identified by the listener. However, a growing number of authors distinguish between speech intelligibility and speech comprehension; intelligibility tests focus on the perception of speech units, whereas speech comprehension tests aim at quantifying the degree to which listeners can interpret the meaning of spoken messages in a communication context (e.g., Fontan, Tardieu, Gaillard, Woisard, & Ruiz, 2015; Hustad, 2008; Wilson & Spaulding, 2010). Intelligibility and comprehension measures may be thought of as complementary because they provide different insights into speech communication. Intelligibility tests yield sensitive and reproducible scores that are mainly dependent on the integrity of the acoustic information present in speech signals. In contrast, the contextual information present in comprehension tests allows listeners to compensate for losses of acoustic information in the speech signal through top-down cognitive processes. Therefore, comprehension scores are less sensitive to small degradations of the speech signal (Lindblom, 1990). They also show a better external validity because they involve processes that are used in everyday communication (Fontan, 2012; Fontan, Gaillard, & Woisard, 2013; Fontan, Tardieu, et al., 2015). Thus, the two kinds of measures might be relevant in professional contexts for which the evaluation of both speech signal transfer and communicative performance is needed. Indeed, it has been shown that performance on one test does not strongly predict performance on the other (Fontan, Tardieu, et al., 2015; Smith, 1992; Smith & Nelson, 2008).

From a practical perspective, both intelligibility and comprehension tests are fairly time consuming, which might limit their clinical use, for example, for the fitting of HAs. In France, audiologists/HA dispensers generally establish speech-processing abilities of their patients/clients by asking them to repeat lists of words (such as those developed by Fournier, 1951). Either a global intelligibility score, corresponding to the percentage of correctly identified words, or the Speech Reception Threshold (SRT), corresponding to the speech level required to obtain 50% correctly identified words, is calculated. In order to establish those HA settings yielding optimal speech intelligibility, the word identification task has to be repeated for each combination of HA settings. Such prolonged testing can result in increased levels of fatigue in the generally older patients/clients, leading to lower identification performance.

Moreover, it has been shown that speech intelligibility scores depend on the listener's familiarity with the speech material (e.g., Hustad & Cahill, 2003). Hence, in theory, speech material should only be used once with the same patient/client, thus limiting the number of combinations of HA settings that can be tested.

To overcome these issues, automatic speech recognition (ASR) could be used to predict speech-processing performance. Indeed, ASR systems have been shown to yield good predictions of human intelligibility and comprehension performance of disordered speech by listeners with normal hearing (e.g., Fontan, Pellegrini, Olcoz, & Abad, 2015; Maier et al., 2009; Schuster et al., 2006). However, to the best of the authors' knowledge, this is the first time that an ASR system is used to predict speech intelligibility and comprehension performance in listeners with simulated ARHL.

Context and Objective of the Present Study

This study is part of a larger research project bringing together language and computer scientists and ear, nose, and throat specialists.[1] The long-term goal of this project is to develop a clinical tool allowing audiologists/HA dispensers to predict speech intelligibility and comprehension for listeners experiencing ARHL in order to facilitate and improve HA fitting. More specifically, the system to be developed would allow recording speech stimuli (e.g., lists of words) in the patient's ear canal near the eardrum, both when wearing a HA and without a HA. The recorded speech is then processed in order to mimic the perceptual consequences of the hearing loss experienced by the patient/client, based on his/her auditory data (e.g., audiogram). The resulting audio signals are then fed to an ASR system that tries to recognize the original speech stimuli. The ASR results (e.g., word error rate [WER]; phonological distances between stimuli and ASR results) and the associated confidence scores are used to predict the intelligibility and comprehension scores human listeners would obtain in the same conditions.

As a first step to reach this goal, several experiments were conducted to study the ability of an ASR system to predict intelligibility and comprehension observed in young participants with normal hearing who are listening to speech processed to simulate ARHL at various levels of severity. This experimental design allowed the same stimuli to be presented to the human listeners and to the ASR system. In addition, it was reasoned that the use of young listeners would reduce the influence of individual differences in cognitive functions (such as working memory) on speech perception (Füllgrabe & Rosen, 2016b) that has been found in older listeners (e.g., Füllgrabe et al., 2015; Füllgrabe & Rosen, 2016a).

Method

Assessment of Human Intelligibility and Comprehension Scores

Speech Material

Word and sentence materials. The material used for the intelligibility tests consisted of 60 words (six lists of 10 words), taken from the intelligibility test developed by Fournier (1951) and widely used by French audiologists/HA dispensers, and of 60 sentences (three lists of 20 sentences),

[1] French Occitanie/Pyrénées-Méditerranée region's AGILE-IT project Grant 12052648 (2012–2015): "Mesure de la compréhension de la parole: équipement électronique intelligent de mesure de la compréhension de la parole basé sur une approche cognitive sur l'exemple de la compréhension humaine."

taken from the French version of the Hearing in Noise Test (HINT; Vaillancourt et al., 2005). Word lists exclusively contained disyllabic masculine nouns preceded by the French definite article "*le*." Sentences consisted of various but rather simple syntactic structures forming single assertive clauses.

The material used for the comprehension test consisted of 30 imperative sentences asking the listener to move virtual objects presented on a computer screen via a click-and-drag action with the computer mouse. These oral commands all matched the following lexico-syntactic pattern:

Mettez [Object 1] [position] [Object 2]
(Move [Object 1] [position] [Object 2]),

where [Object 1] and [Object 2] corresponded to mono- or polysyllabic nouns, and [position] referred to one out of the four spatial prepositions: *à droite de* ("to the right of"), *à gauche de* ("to the left of"), *au-dessus de* ("above"), and *au-dessous de* ("under"). Example sentences are: *Mettez la feuille à gauche du chapeau* ("Move the leaf to the left of the hat") or *Mettez la loupe au-dessus du slip* ("Move the magnifying glass above the underpants").

For each intelligibility and comprehension test, 10 additional items were presented prior to data collection for training purposes.

Speech recordings. Recordings took place in an audiometric booth[2] using an omnidirectional Sennheiser MD46 microphone (Sennheiser, Wedemark, Germany) and a TASCAM DM-3200 mixing console (TEAC Corporation, Tokyo, Japan). Each of three native French speakers (a 12-year-old girl, a 46-year-old man, and a 47-year-old woman) produced all 70 words and 110 sentences. Hence, the entire corpus comprised 210 words and 330 sentences and had a total duration of 12 min. In order to equalize the loudness of the recorded words and sentences, three of the authors adjusted the level of each word and sentence relative to a reference item, and the mean gain values of the adjustments were applied to the stimuli.

Simulation of ARHL. The algorithms described by Nejime & Moore (1997) were used to simulate some of the perceptual consequences of ARHL, using a custom-written MATLAB program (MathWorks, 2015). The program uses the audiometric thresholds as input data. Here, nine levels of hearing-loss severity were simulated. This was done by using the mean audiograms observed for the 3,753 older participants of the Beaver Dam study, grouped into nine age groups with mean ages ranging between 60 and 110 years (Cruickshanks et al., 1998). Figure 1 shows the best polynomial regression curves obtained for fitting mean hearing thresholds at 15 frequencies ranging from 125 Hz to 16 kHz.

Based on the audiometric input data, the program simulates three effects associated with ARHL: (a) reduced audibility (by filtering several frequency bands according to the audiogram values given as an input); (b) reduced frequency selectivity (by spectrally smearing the speech signal; Baer & Moore, 1993); (c) loudness recruitment (by raising the signal envelope; Moore & Glasberg, 1993).

To simulate the reduction of frequency selectivity, the program first defines the degree of hearing loss (mild, moderate, or severe) based on the pure-tone average for audiometric frequencies between 2 and 8 kHz. Three different degrees of spectral smearing are then applied, depending on the degree of hearing loss.

In this study, only one simulation of loudness recruitment was used; the envelope of the speech signal was raised in order to simulate the effect of moderate loudness recruitment (Moore & Glasberg, 1993). This choice made loudness recruitment subject to a high intersubject variability (Moore, 2007); therefore, the level of recruitment cannot be predicted on the sole basis of age and auditory thresholds.

The nine conditions of simulated thresholds, loudness recruitment, and loss of frequency selectivity are shown in Table 1, with corresponding theoretical ages.

The speech corpus was processed to simulate the effects of ARHL at nine levels of severity, resulting in 1,890 word stimuli and 2,970 sentence stimuli (approximate total corpus duration: 115 min). These levels are referred to as ARHL-simulation conditions 1 to 9 in the remainder of the article.

Participants

Sixty university students (34 women, 26 men) ages 18 to 30 years (mean age = 21.3 years; standard deviation = 2.2) took part in this study in exchange for monetary compensation. All were native French speakers and had hearing thresholds ≤ 15 dB HL at 250, 500, and 1000 Hz, and average audiometric thresholds < 15 dB HL for frequencies of 2, 4, and 8 kHz (the latter complied with the definition of no ARHL in the program used to simulate the effects of ARHL). None of the participants reported any uncorrected vision problem.

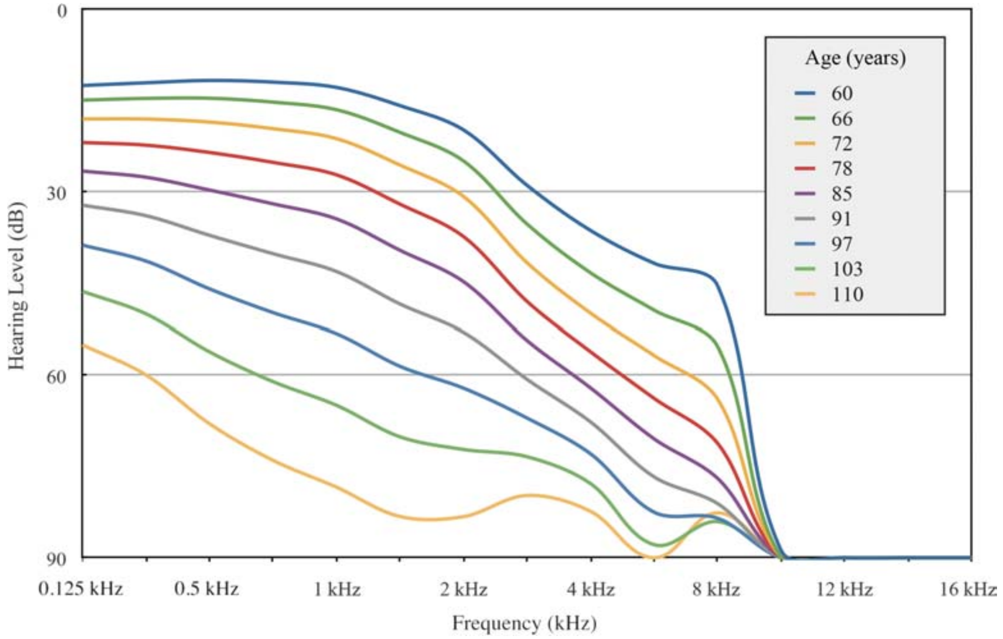
Procedure

Participants completed two intelligibility tests (referred to as IT1 and IT2) and one comprehension test (referred to as CT). They were separated in two groups: Half of the participants completed IT1 and CT, whereas the other half completed IT2 and CT. Consequently, both IT1 and IT2 were completed by 30 participants, whereas CT was completed by all 60 participants. For both participant groups, the order between intelligibility and comprehension tests was counterbalanced. The nine ARHL-simulation conditions were also counterbalanced.

Each participant completed the tests individually in a double-walled sound-attenuating booth (ambient noise level: 28-dB, A-weighted). The participant was seated in front of two Tannoy Precision 6D loudspeakers (Tannoy Ltd., Coatbridge, Scotland, UK), placed at a distance of approximately one meter and at ± 30° azimuth relative to the listener. Speech level was calibrated so that the level of the unprocessed speech stimuli (i.e., stimuli that had not undergone the ARHL-simulation process) reached, on average, 60 dB (A-weighted) at the participant's ear.

[2] http://petra.univ-tlse2.fr

Figure 1. Regression curves fitting mean hearing thresholds for nine mean ages as a function of tone frequency, according to Cruickshanks et al. (1998).



Intelligibility Tests

Participants were asked to repeat what they had heard (words in IT1 and sentences in IT2) into a microphone positioned in front of them. They were encouraged to guess in case they were unsure about what had been presented. Responses were recorded to be transcribed and scored offline by three of the authors. For IT1, a response was judged as “correct” if it matched every phoneme of the target word, and “incorrect” otherwise (binary score). For IT2, the score for each sentence was calculated as the number of correctly identified words divided by the total number of words in the sentence. The final intelligibility scores were calculated as the total percentage of correct responses for each test.

Comprehension Test

Participants were seated facing a 20-in. color monitor displaying six images (evenly distributed into two rows

Table 1. Experimental conditions of age-related hearing loss simulated for ages between 60 and 110 years and associated absolute thresholds, level of loudness recruitment, and reduction of frequency selectivity.

	Condition no.								
Parameter	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Theoretical age (years)	60	66	72	78	85	91	97	103	110
Loudness recruitment	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate
Reduction of frequency selectivity	Mild	Moderate	Moderate	Moderate	Severe	Severe	Severe	Severe	Severe
					Simulated thresholds (dB HL)				
0.125 kHz	12	15	18	22	27	32	39	46	55
0.250 kHz	12	15	18	22	28	34	41	50	60
0.500 kHz	12	15	19	24	30	37	46	56	68
0.750 kHz	12	15	20	25	32	40	50	61	74
1.000 kHz	13	16	21	27	34	43	53	65	78
1.500 kHz	16	20	26	32	40	48	59	70	83
2.000 kHz	20	25	31	37	45	53	62	72	83
3.000 kHz	29	35	42	48	54	61	67	73	80
4.000 kHz	36	43	50	56	62	68	73	78	82
6.000 kHz	42	49	57	64	70	77	83	88	90
8.000 kHz	45	55	64	71	77	81	84	84	83

and three columns) for each sentence that was played (see Figure 2 in Fontan, Tardieu, et al., 2015). They were asked to respond to each command by selecting and then dragging a target image (Object 1) above/below/to the right of/to the left of another target image (Object 2). A computer mouse was used to perform these actions. Each sentence was considered as understood if the three key elements (Target Image 1, position, Target Image 2) were correctly identified by the listener, based on the actions that were performed on the computer screen. Final CT scores were calculated as the percentage of sentences correctly understood by the listeners in each of the nine ARHL-simulation conditions.

Computing Automatic Intelligibility and Comprehension Scores

In contrast to most research in the field of ASR that has the goal to design the best possible system (in terms of WER), the present work aimed at developing an ASR system that would simulate as closely as possible human behavior, even if that resulted in suboptimal performance. To achieve this, an ASR system based on SPHINX-3 (distributed by Carnegie Mellon University; Seymore et al., 1998) and French acoustic models adapted to the three voices were used. The ESTER2[3] audio and text corpus (Galliano, Gravier, & Chaubard, 2009) was used for the creation of the acoustic models and of a trigram language model that together constituted the baseline ASR system. Different configurations for the lexicon and language models were then developed in order to best fit the human scores.

Description of the ASR System

Acoustic Models

The French acoustic models used in this study came from the Laboratoire d'Informatique de l'Université du Maine (France; Deléglise, Estève, Meignier, & Merlin, 2005; Estève, 2009). They included 35 phones and five kinds of pauses and were designed to process 16-kHz audio samples based on a Perceptual Linear Predictive feature extraction (Hermansky, 1990). Acoustic models were trained upon the basis of French radio broadcasts (Galliano et al., 2009) and were formed by 5,725 context-dependent states (senones) with 22 Gaussian mixtures per state.

Speaker Adaptation

The acoustic models were trained on recordings that included more male than female voices (Galliano et al., 2006). This caused the system to show a better WER for the male than for the female and child speaker. As a consequence, a first step of the present work was to adapt the ASR system to the voices of the speakers in order to obtain ASR performances as similar as possible (in terms of WER) for the adult-male, adult-female, and child speech. To this end, the vocal-tract-length normalization technique (VTLN; Wegmann, McAllaster, Orloff, & Peskin, 1996) was used. The VTLN technique is based on the assumption that there is a direct linear relationship between speech formant areas and the vocal tract length of the speaker. It consists of determining the best warping factor λ that maximizes the likelihood of the phones produced by a specific speaker:

$$\lambda = \arg\max P(0|X, \lambda_k), \qquad (1)$$

where X is the observation and k the index of the kth frequency warping factor considered. In order to find the best λ value for each of the three speakers, the inverse linear function $y = x/\lambda$ was used and tested on the IT1 subcorpus. Results showed that the adult-male speaker recordings did not need any adaptation (λ = 1.0), whereas the adult-female speaker and the girl speaker recordings needed VTLN with optimal λ values of 1.84 and 2.24, respectively. These two warping factors were systematically used for the extraction of female and child speech features during automatic speech recognition.

Lexicon and Language Models

The lexicon and language modeling constituted the main stage in the fitting of the ASR scores to human scores. Based on the assumption that human performance is greatly influenced by top-down expectations at lexical, syntactic, and contextual levels, the goal was to feed the system with similar lexical and syntactic cues to constrain its behavior and thus to get a better linear correlation with human data.

To this end, different ways of modeling the lexicon and syntax were explored for each of the three tests, and the results compared to those obtained with the baseline model. The latter contained very low constraints upon the lexicon and syntactic structures to be recognized; it is a trigram language model calculated on the basis of the ESTER2 corpus (Deléglise et al., 2005; Galliano et al., 2009) associated with a 62,000-word lexicon and is henceforth referred to as BM.

For IT1, one additional language model was designed in order to reflect the syntactic, lexical, and phonological properties of the test stimuli. This model, referred to as IT1M, is a bigram language model based on the syntactic structure [Det + Noun], and its lexicon contains only disyllabic masculine nouns beginning with a consonant (15,000 forms). To reflect the frequency of these forms in oral French, the frequency values defined by New, Brysbaert, Veronis, and Pallier (2007), based on movie subtitles and available in the database Lexique 3.8,[4] were used.

For IT2, four additional language models were designed:

- IT2M1 is a trigram language model, based on a subcorpus of ESTER2; this subcorpus consists of the ESTER2 utterances containing at least one word occurring in IT2 sentences.

[3] Évaluation des Systèmes de Transcription Enrichie d'Emissions Radiophoniques (Evaluation of Broadcast News Enriched Transcription Systems)

[4] http://www.lexique.org

- IT2M2 is the same trigram model as BM, but with a lexicon restricted to the words constituting the 260 sentences of the complete French version of the HINT.
- IT2M3 is the same trigram model as BM, but with a lexicon restricted to the words constituting the 60 HINT sentences included in the IT2 test.
- IT2M4 is an finite-state grammar (FSG), allowing the generation of the 60 HINT sentences included in the IT2 test.

Finally, two additional language models were designed for CT:

- CTM1 is an FSG, allowing the generation of all the possible combinations in the CT test, that is, around 50,000 sentences (112 objects × 4 positions × 111 objects);
- CTM2 is the same FSG as CTM1, but associated with a dynamic lexicon; for each sentence processed by the ASR system, only the nouns corresponding to the six images actually presented to the listeners during CT were included in the lexicon.

Table 2 summarizes the different language models used for the automatic recognition.

ASR-Score Calculation. For the recognition of the intelligibility-test items (words and sentences for IT1 and IT2, respectively) only the percentage of correct words was considered as an outcome measure. The determinant “le” was not taken into account for IT1 items in order to follow the scoring procedure used with human participants. For the recognition of CT items, only the recognition of the three main keywords of each sentence (i.e., Object 1, position, Object 2) was considered and the ASR score corresponds to the percentage of sentences for which all keywords were recognized by the system.

Results

Word Intelligibility Test (IT1)

Word-identification performance for the human listeners and the ASR system using two different language models are presented in Figure 2 as a function of simulated-ARHL condition. The different panels show average results for each of the three speakers and the grand average.

Human word identification declines sigmoidally with increasing severity of the simulated ARHL condition, with, on average, Conditions 1 and 2 and Conditions 8 and 9 yielding ceiling and floor effects, respectively.

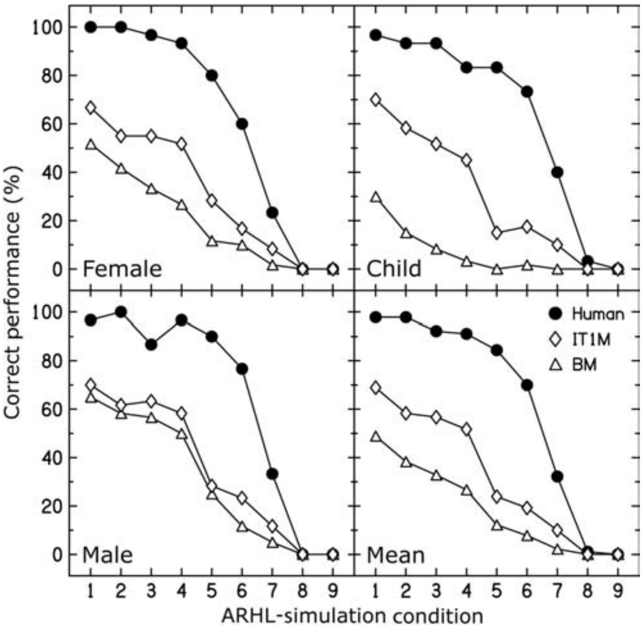
Machine scores are generally lower than human scores (mean: 63%), with IT1M yielding higher scores (mean: 32.1%) than BM (mean: 18.8%), but also followed a downward trend with increasing ARHL-simulation condition. However, the shape of the performance functions for the two language systems differs from that for human listeners (e.g., it is linear for BM/female and concave for BM/child). Marked decreases in performance can be seen

Table 2. Language models used for the automatic recognition of Intelligibility Test 1 (IT1), Intelligibility Test 2 (IT2), and Comprehension Test (CT) stimuli.

Model	Description
Baseline model (BM)	Trigrams (ESTER2 corpus) and 62,000-word lexicon
IT1	
IT1M	Bigrams (Det + N) with word frequencies based on Lexique 3.8
IT2	
IT2M1	Trigrams calculated on a subcorpus of ESTER2
IT2M2	BM trigrams with a lexicon restricted to that of the 260 HINT sentences
IT2M3	BM trigrams with a lexicon restricted to that of the 60 IT2 sentences
IT2M4	FSG allowing the generation of the 60 IT2 sentences
CT	
CTM1	FSG allowing the generation of the ~50,000 sentences possibly combined in CT
CTM2	Same FSG as CTM1 associated with a dynamic lexicon

Note. HINT = Hearing in Noise Test; FSG = finite-state grammar.

Figure 2. Word intelligibility for Intelligibility Test 1 (IT1) as a function of the condition of simulated age-related hearing loss (ARHL) for human listeners (filled circles) and the automatic speech recognition (ASR) system, using different language models (see open symbols in the figure legend). The different panels show results for each of the three speakers (female, child, and male) and averaged across speakers (mean). BM = baseline model.



between Conditions 1 and 2 and Conditions 4 and 5. On average, the highest machine scores are obtained for the male speaker (mean$_{\text{BM}}$: 30.2%, mean$_{\text{IT1M}}$: 35.2%), then the female speaker (mean$_{\text{BM}}$: 19.6%, mean$_{\text{IT1M}}$: 31.3%), and finally the child speaker (mean$_{\text{BM}}$: 6.5%, mean$_{\text{IT1M}}$: 29.7%).

To establish the goodness-of-fit of the machine scores for human word intelligibility as a function of ARHL-simulation condition, Pearson's linear correlation coefficient was computed for each combination of language model and speaker condition (see Table 3). Given the existence of floor and ceiling effects, scores were first transformed into rational-arcsine units (RAUs; Studebaker, 1985). As expected based on the visual inspection of the results, all correlations were positive, strong (ranging from .71 to .99), and significant (all $p \leq .032$, two tailed). Comparing correlation coefficients for the ASR system using the two different language models, after applying Fisher's r-to-z transformation, revealed a significant difference (i.e., improvement in the strength of the correlation) between BM and IT1M only for the child speaker ($z = -2.95$, $p = .002$, one tailed; a one-tailed test was used because it was assumed that BM would yield lower correlation coefficients than the more "sophisticated" models).[5] The left panel of Figure 3 shows the scatterplot relating mean RAU-transformed human and machine scores for the BM and the best linear fit. Because ASR performance is lower than human performance for all conditions, all data points (except for the most severe ARHL-simulation condition yielding the lowest possible RAU score for listeners and the ASR system) fall above the diagonal that indicates identical performance for both the human and machine listener.

Sentence Intelligibility Test (IT2)

Sentence-identification performance for the human listeners and the ASR system using five different language models are presented as a function of simulated-ARHL condition in Figure 4.

As for word identification, human sentence identification declines sigmoidally with ARHL-simulation condition, with the ceiling effect extending up to and including Condition 4. On average, identification for sentences (mean: 64.6%) was very similar to that for words.

The ASR system generally yields lower than human scores, independently of the language models used (mean performance ranges from 30.9% to 51.8%), which, consistent with the human results, decline with ARHL-simulation condition. However, the shape of these functions differs from that of human performance; marked decreases are again observed between Conditions 4 and 5 for all language models, and, for IT2M4, performance for Conditions 8 and 9 is actually better than human performance. Across all ARHL simulations and language models, the male speaker yields the highest machine scores (mean: 46.6%), the female speaker the second highest (mean: 40.2%), and the child speaker the lowest (mean: 35%).

Table 3. Pearson's correlation coefficients for Intelligibility Test 1 (IT1) between human intelligibility scores and automatic speech recognition (ASR) scores, using different language models and for all speakers combined (mean) or individual speakers.

	Speaker			
Model	**Mean**	**Male**	**Female**	**Child**
BM	.94 (.000)	.93 (.000)	.97 (.002)	.71 (.032)
IT1M1	.97 (.000)	.95 (.000)	.99 (.000)	.93 (.000)**

Note. p values for two-tailed t tests are given in parentheses. Asterisks indicate the p values for one-tailed tests of the difference between the correlation coefficient for the baseline model (BM) and each of the other language models. All tests were uncorrected for multiple comparisons.

**$p < .01$; one-tailed test re: BM.

Table 4 indicates Pearson's linear correlation coefficients between RAU-transformed human and machine scores for the different language models and speakers. All correlations were positive, strong (ranging from .90 to .99), and significant (all $p \leq .001$, two tailed). Compared to the correlation coefficient obtained for the BM—and when averaging performance across speakers—the four other language models yield significantly stronger correlations (all $z \geq -2.37$, all $p \leq .009$, one tailed). However, when considering performances for each speaker individually, some models did not yield a significant improvement in the strength of the correlation (IT2M1 with the male speaker and IT2M2 and IT2M4 with the female speaker).

The middle panel of Figure 3 shows the scatterplot relating mean RAU-transformed human and machine scores for the BM and IT2M4 (which yielded significantly higher correlation compared to the BM) and the best linear fits. The regression lines for the BM and IT2M4 have comparable slopes; however, the y-intercept of the regression line is higher with the BM than with IT2M4, showing that the difference between human and ASR scores is reduced for IT2M4. For both BM and IT2M4, the regression lines present degrees of incline > 45 degrees, showing that the differences between human and ASR performances tend to increase with the elevation of scores.

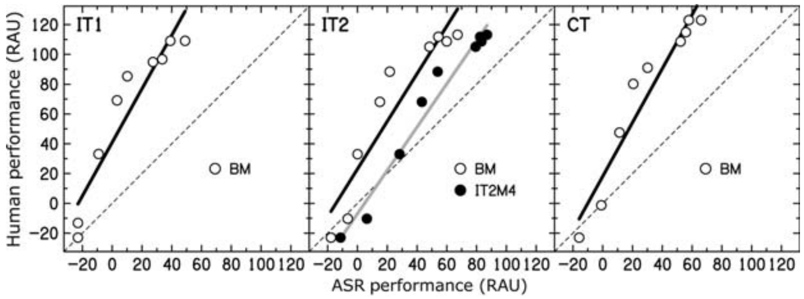
Comprehension Test (CT)

Comprehension performance for the human listeners and the ASR system using three different language models are presented as a function of simulated-ARHL condition in Figure 5.

Human speech comprehension (mean: 68.7%) is only slightly better than word and sentence identification but shows a similar dependence on ARHL-simulation condition and extent of the ceiling effect.

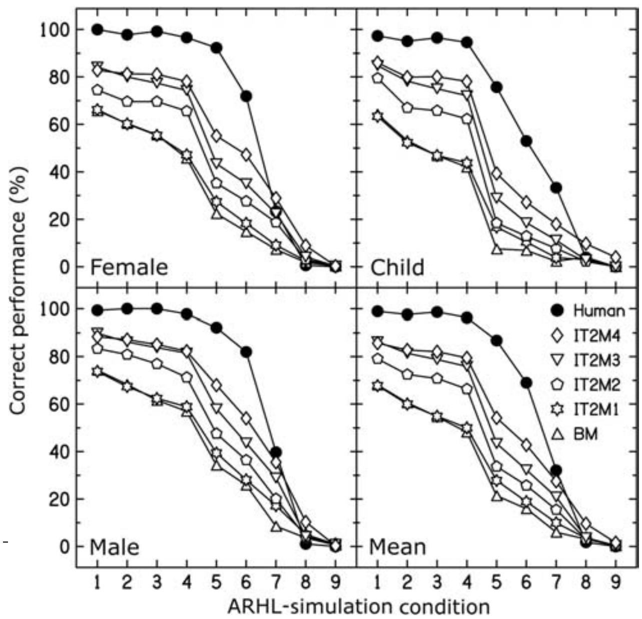
[5] The calculation of the significance of the difference between the two correlations was checked according to Steiger (1980) on the online software made available by Lee and Preacher (2013).

Figure 3. Scatterplots relating the mean rational-arcsine unit (RAU)-transformed human scores to RAU-transformed machine scores obtained in each of the three speech tests, Intelligibility Test 1 (IT1), Intelligibility Test 2 (IT2), and Comprehension Test (CT). Results for the baseline model (BM) and a more sophisticated language model (IT2M4) showed a significant improvement in the strength of the correlation. ASR = automatic speech recognition.



Machine scores increased from BM (mean: 33.6%) over CTM2 (mean: 54.7%) to CTM1 (mean: 68%) but are lower than human scores. Once again, a marked decline in performance is observed between ARHL-simulation conditions 4 and 5. Interestingly, both more sophisticated language models (especially CTM1) yield performance for the most severe ARHL conditions that exceeds that observed in human listeners. Across all ARHL simulations and language models, highest machine performance was observed for the male speaker (mean: 57.3%), then the child speaker (mean: 51.2%), and finally the female speaker (mean: 47.8%).

Figure 4. Sentence intelligibility for Intelligibility Test 2 (IT2) as a function of the condition of simulated age-related hearing loss (ARHL) for human listeners (filled circles) and the automatic speech recognition (ASR) system, using different language models (see open symbols in the figure legend). The different panels show results for each of the three speakers (female, child, and male) and averaged across speakers (mean). BM = baseline model.



Pearson's correlation coefficients between RAU-transformed human and machine scores, presented in Table 5, were positive, strong (ranging from .91 to .98), and significant (all $p \leq .001$, two tailed). Compared to BM, both more sophisticated models CTM1 and CTM2 do not yield significantly stronger correlations with human scores for any of the speaker conditions. The right panel of Figure 3 shows the scatterplot relating mean RAU-transformed human and machine scores for the BM and the best linear fit. The *y*-intercept of the regression line is almost situated on the diagonal indicating identical performance for both the human and machine listener. However, for higher scores, the difference between human and ASR performance tends to increase.

Discussion

The long-term goal of this research work is to develop an ASR-based system able to predict human speech-processing performance, with the purpose of facilitating HA fitting for people with ARHL. The current study constituted the first step toward this goal by comparing ASR results to speech intelligibility and comprehension scores of young participants with normal hearing who are listening to speech processed to simulate ARHL.

The observed strong correlations for all three tests and all speaker conditions indicate that the ARHL simulation, representing the different levels of severities of the perceptual consequence of hearing loss associated with ages 60 to 110 years, had comparable effects on human and ASR scores. Thus, it appears that ASR systems could be used to predict trends in human speech intelligibility and comprehension with increasing level of ARHL.

However, weaker machine scores were generally found when processing words and sentences uttered by the female and child speakers than those uttered by the male speaker. This is probably due to the acoustic models used in this study. They were trained on speech recordings consisting of two thirds male voices (Galliano et al., 2006).

Table 4. Pearson's correlation coefficients and associated *p* values (in parentheses) for Intelligibility Test 2 (IT2) performance between human intelligibility scores and automatic speech recognition (ASR) scores, using different language models and for all speakers combined (mean) or individual speakers.

	Speaker			
Model	**Mean**	**Male**	**Female**	**Child**
BM	.94 (.000)	.95 (.000)	.94 (.000)	.90 (.001)
IT2M1	.96 (.000)**	.97 (.000)	.96 (.000)*	.94 (.000)**
IT2M2	.97 (.000)**	.97 (.000)**	.97 (.000)	.95 (.000)***
IT2M3	.98 (.000)**	.98 (.000)*	.97 (.000)*	.97 (.000)***
IT2M4	.99 (.000)***	.99 (.000)*	.98 (.000)	.96 (.000)***

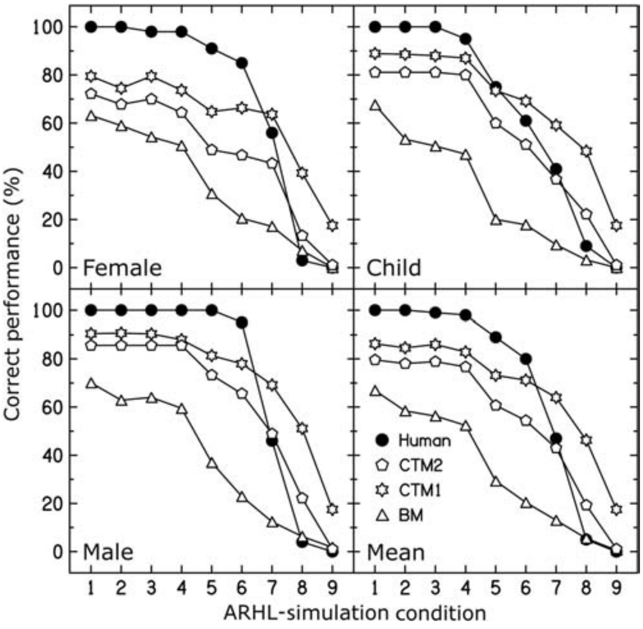
Note. BM = baseline model.

*$p \leq .05$; **$p < .01$; ***$p \leq .001$; one-tailed test re: BM.

Although the VTLN technique (Wegmann et al., 1996) was used to adapt the ASR system to the different voices, the results indicate that this did not fully eliminate interspeaker differences.

In order to obtain the strongest associations possible between ASR scores and human performance, several language models were designed by taking into account the phonological, lexical, syntactic, and extralinguistic cues that underlie human performance in IT1, IT2, and CT. A model with very low constraints on the lexicon and syntactic structures (BM) was used to generate machine baseline performance against which improvements due to the different, more sophisticated language models could be measured.

Figure 5. Speech comprehension (for the Comprehension Test [CT]) as a function of the condition of simulated age-related hearing loss (ARHL) for human listeners (filled circles) and the automatic speech recognition (ASR) system, using different language models (see open symbols in the figure legend). The different panels show results for each of the three speakers (female, child, and male) and averaged across speakers (mean). BM = baseline model.



Apart from IT2, model sophistication did not yield significant improvements in the strength of the association between machine and human scores. A possible partial explanation for this finding is that the correlation between human and BM scores was already very high (≥ .90 except for IT1 and the child speaker), and this left little room for improvements. When looking at the conditions yielding the lowest correlations with BM (e.g., child speech conditions in IT1 and IT2), highly significant improvements were observed when using more sophisticated models.

Floor and ceiling effects were observed in the human performance for all three speech tests. However, the number of ARHL-simulation conditions that were affected varied with the test used, with CT > IT2 > IT1 as regards ceiling effects, and IT1 > IT2 > CT as regards floor effects. This observation is consistent with the assumption that contextual effects have an increasingly beneficial effect on human performance as speech processing goes from word identification over sentence identification to comprehension (Lindblom, 1990; Fontan, Tardieu, et al., 2015). The aim of the present study was to explore the effect of the full range of levels of ARHL (from mild to severe) on speech processing in quiet. The existence of floor and ceiling effects was therefore unavoidable. The application of a RAU transformation to the raw data allowed us to overcome the problems associated with such effects, at least to some extent.

To enhance the performance of the prediction system and to extend its applicability to other groups of listeners

Table 5. Pearson's correlation coefficients and associated *p* values (in parentheses) for Comprehension Test (CT) performance between human intelligibility scores and automatic speech recognition (ASR) scores, using different language models and for all speakers combined (mean) or individual speakers.

	Speaker			
Model	**Mean**	**Male**	**Female**	**Child**
BM	.96 (.000)	.91 (.001)	.95 (.000)	.98 (.000)
CTM1	.97 (.000)	.95 (.000)	.96 (.000)	.98 (.000)
CTM2	.98 (.000)	.97 (.000)	.98 (.000)	.98 (.000)

Note. BM = baseline model.

and to other listening conditions, the following lines of research will be pursued in the future.

1. Acoustic models will be trained on speech corpora containing a balance of male and female adult and child voices. Also, because the main difficulty of people experiencing ARHL is to understand speech in the presence of interfering sounds, the applicability of these models to the recognition of speech in adverse listening conditions (e.g., background noise, reverberation) needs to be assessed. Whether our findings can be generalized to other languages than French also needs to be established.
2. In the present study, the goodness-of-fit of the prediction by machine scores of the observed trends in average human performance for a range of simulated ARHL conditions was quantified. Because the ultimate aim of the system is to help audiologists/HA dispensers with the fitting of HAs to individual patients/clients, the system's predictive power of individual cases of ARHL needs to be tested. Also, the present study used young listeners with normal hearing for whom ARHL was simulated. This choice was made so that the same stimuli could be presented to the participants and to the ASR system. However, the participants tested in the present study differed considerably from the population for which the prediction system was originally designed, namely people with ARHL who are generally older. Performance in many cognitive abilities declines with age (for example, in working memory, attention, processing speed, inhibition; e.g., Füllgrabe et al., 2015; Park et al., 2002). In addition, age-related changes in supraliminary auditory processing are observed in older listeners, for example in the processing of temporal–fine structure (Füllgrabe, 2013; Füllgrabe et al., 2015; Grose & Mamo, 2010; Moore, Glasberg, Stoev, Füllgrabe, & Hopkins, 2012) and temporal-envelope information (Füllgrabe, Meyer, & Lorenzi, 2003; Füllgrabe et al., 2015; He, Mills, Ahlstrom, & Dubno, 2008). As both temporal processing and cognitive abilities are associated with speech-in-noise perception (e.g., Füllgrabe et al., 2015), it is probably necessary to consider these abilities in future versions of the ASR-based prediction system to yield accurate predictions of speech-perception performance for all listeners across the adult lifespan.
3. The simulations of ARHL used to produce the degraded input to the prediction system might have to be refined. For example, in the current study, the simulation of loudness recruitment was fixed at one severity condition corresponding to a moderate level of loudness recruitment. This choice was made because the severity of loudness recruitment is highly variable among people experiencing ARHL (Moore, 2007). However, this restriction has a potential impact on the ability of the system to accurately predict speech intelligibility and comprehension for older people presenting different degrees of loudness recruitment. In a next step, the level of loudness recruitment should be manipulated in order to verify that its effect on ASR scores is comparable to its effects on human speech recognition performance. In addition, strong decreases in ASR scores were observed between ARHL-simulation conditions 4 and 5, and, to a lesser extent, between ARHL-simulation conditions 1 and 2. These decreases in performance are probably caused by the spectral smearing, which simulated the consequences of losses in frequency selectivity on speech perception. As shown in Table 1, going from ARHL-simulation conditions 1 to 2 and from 4 to 5 coincides with a change in the simulated severity of the loss of frequency selectivity. No comparable effect was observed in the human scores, consistent with results reported by Baer and Moore (1993), showing that the spectral-smearing algorithm had a significant effect on speech intelligibility only when stimuli were heard in noisy conditions. This matter warrants further investigation on the use of an ASR-based system to predict human processing performance for spectrally smeared speech presented in noise.
4. To further address the role of top-down effects on speech processing, future work will investigate different test materials and tasks from those used in the present study. For example, nonsense or low-predictable sentences such as those used in the Matrix test (Vlaming et al., 2011) could be used to eliminate the syntactic and semantic predictability present in the sentences used in IT2 and CT. Also, using sentences requiring the listener to process other linguistic cues to interpret the meaning of the sentences (e.g., thematic roles) could be relevant.
5. Finally, this research concentrated on correlations between machine and humans scores, that is, on the predictability of the trends observed in human speech intelligibility and comprehension. Further research is needed to assess the ability of the ASR system to predict actual intelligibility and comprehension scores. Also, in addition to the purely quantitative prediction, it would be of interest to investigate whether qualitative aspects of human speech processing can be predicted by the ASR system. For example, the analysis of the phonetic confusions predicted by the ASR system might provide insights into which acoustic features are misperceived by human listeners (Fontan, Ferrané, Farinas, Pinquier, & Aumont, 2016; e.g., predicting that with a specific HA setting the listener will tend to perceive stop consonants as their constrictive counterparts). This information might prove very helpful to audiologists/HA dispensers for the fine-tuning of HAs.

Taken together, our results indicate that ASR-based prediction systems are able to provide good estimates of the trends in human speech-processing abilities that can be seen with increasing levels of ARHL. In the future, this might help to optimize the fitting process of HAs in terms of the time necessary to find optimal HA settings and the amount of benefit derived from HAs, and therefore reduce their rejection by people experiencing ARHL.

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