The Iowa Test of Consonant Perception

Validation of the Iowa Test of Consonant Perception

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Abstract

Speech perception (especially in background noise) is a critical problem for hearing-impaired listeners, and an important issue for cognitive hearing science. Despite a plethora of standardized measures, few single-word closed-set tests uniformly sample the most frequently used phonemes and use response choices that equally sample phonetic features like place and voicing. The Iowa Test of Consonant Perception (ITCP) attempts to solve this. It is a proportionally balanced phonemic word recognition task designed to assess perception of the initial consonant of monosyllabic consonant-vowel-consonant (CVC) words. The ITCP consists of 120 sampled CVC words. Words were recorded from four different talkers (two female) and uniformly sample from all four quadrants of the vowel space to control for coarticulation. Response choices on each trial are balanced to equate difficulty and sample a single phonetic feature. This study evaluated the psychometric properties of ITCP by examining reliability (test-retest) and validity in a sample of online normal hearing participants. Ninety-eight participants completed two sessions of the ITCP along with standardized tests of words and sentence in noise (CNC words and AzBio sentences). The ITCP showed good test-retest reliability and convergent validity with two popular tests presented in noise. All the materials to use the ITCP, or to construct your own version of the ITCP are freely available here: <https://osf.io/hycdu/>.

Keywords: auditory perception, speech-in-noise, closed-set, open-set, validation

I. Introduction

Speech perception is generally successful under ideal circumstances, even as the auditory signal can be acoustically variable due to differences in talker speaking rate and coarticulation. However, listening often takes place under non-ideal circumstances. For instance, background noise from other people and from machines is common, electronic communication can introduce distortions or discontinuities in the overall message, and hearing loss is highly prevalent. Thus, the way people cope with such circumstances is crucial for clinical work and basic science.

In the clinic, the most common challenge reported by hearing-impaired listeners is understanding speech in noise (Hughes et al., 2018). Moreover, from a scientific perspective, speech in noise perception may reveal a host of cognitive and cortical processes that are relevant for speech but cannot be seen otherwise such as grouping features of the acoustic signal that comprise the target speech, suppressing competing background elements, sustaining attention to the target, and filling in missing information (Shinn-Cunningham, in press).

While the basic science of speech perception has often relied on stimuli that were designed to test specific theories of perceptual organization or processing (e.g., Delattre et al., 1955; Ganong, 1980; Remez et al., 1981), there is an equally important role for standardized measures that assess listeners' relative skill at perceiving speech using representative speech materials. This is fundamental for clinical work, but it is increasingly important in areas like cognitive neuroscience. Here, such measures allow researchers to use stimuli that are standardized and representative of speech/speech-in-noise (SiN) in general. This can make it easier to draw inferences across studies that use the same standard tests.

There is a wealth of such tests and materials available (e.g., California Consonant Test [CCT], Owens & Schubert, 1977; the Diagnostic Rhyme Test, Voiers, 1977, 1983); the Hearing

in Noise Test [HINT], Nilsson, Soli, and Sullivan, 1994; the Modified Rhyme Test, House et al., 1965; Words in Noise [WIN], Wilson, 2003; and the QuickSIN, Killion et al., 2004). Speech-in-noise tests can be classified along two broad dimensions: 1) whether stimuli are sentences or words, and 2) whether the response is open- or closed-set. There is no single “best” option for all applications; however, these choices have implications for the inferences that can be made both scientifically and clinically. Within the clinic and the lab, there is a strong zeitgeist toward sentence-based, open-set tests, which are seen as more ecological. However, there is nonetheless a clear need for better single-word, closed-set tests which we argue can address questions that cannot be answered otherwise. Thus, this paper describes and validates the newly developed Iowa Test of Consonant Perception (ITCP). We start by discussing these two core dimensions (i.e., sentences vs. words and open-set vs. closed-set). We then describe the motivation, logic, and development of the ITCP before presenting a validation study.

A. Sentences vs. words

A major difference between sentence- and word-based tests is demand characteristics. The former requires correctly perceiving and repeating entire sentences (or the words within a sentence), while the latter requires identifying (usually repeating out loud) a single word.

Sentence-based tests are generally seen as more predictive of outcomes for people with hearing impairment. Sentence-based tests are arguably more ecologically valid and more representative of real-world listening (e.g., human conversation). Because of this, for clinical purposes at least, they are increasingly preferred over single word-based tests (Taylor, 2003).

Despite these arguments, sentence-based tests have two issues that may limit their use in certain circumstances. First, at a purely auditory level, the phonemes of English (or any other language) span many frequency ranges (Nakajima et al., 2017) and many types of acoustic cues

(rapidly changing vs. steady-state, harmonic vs. aperiodic, etc.). These, in turn, are shaped by neighboring sounds through coarticulation. Given the constraints on constructing reasonable sentences, it may be difficult to sample this space uniformly, and some classes of sounds or some coarticulatory contexts may be over- or under-assessed. This prevents such measures from offering a truly representative measure of one's skill at speech perception and prevents them from providing fine-grained diagnostic information about specific perceptual weaknesses.

Second, performance on sentence-based tests depends on several cognitive factors unrelated to hearing. Perhaps the most common factor is context (Conrad, 1974). For example, in the sentence, "She got a loaf of bread from the...", a listener can likely figure out that the last word is "bakery" without hearing it. This sentence has a highly predictable context. However, even sentences that are not predicable from context, which capture more bottom-up auditory processing, can contain a lot of additional information that constrains perception. For example, something as simple as a determiner ("the" or "a") can limit the range of lexical choices from about 42,000 (the number of words in the average lexicon: Brysebaert, et al., 2016) to maybe 15,000 (just nouns or adjectives).

Moreover, sentence comprehension is a complex process in its own right. Indeed, entire fields of cognitive science are devoted to understanding sentence processing in quiet. Some sub-mechanisms like segmentation and prosody are highly perceptually based and cannot be measured with isolated words (Salverda et al., 2003; Dilley & Pitt, 2010). However, other processes are only indirectly related to auditory perception. These include language-specific processes bundled together as "sentence processing" which include parsing syntax, assigning thematic roles to words, and establishing the referents of nouns and pronouns (see Tanenhaus and Trueswell, 1995; Altmann, 1998 for reviews). Even at the level of recognizing the individual

words in a sentence, the time demands created by sentences may challenge the system further as listeners must recognize words rapidly as subsequent words may be unfolding. Finally, domain-general processes like working memory and cognitive control are correlated with sentence processing (Just & Carpenter, 1992; Novick et al., 2005). In fact, the ability to hear a sentence in quiet and repeat it is so consistently impaired in Developmental Language Disorder (a disorder for which a hearing impairment is disqualifying) that it is considered a strong diagnostic feature (Redmond et al., 2019). Thus, as a basis for measuring speech perception, sentence materials tap into far more than speech perception.

The fact that all these processes contribute is likely why sentence-based tests are generally more predictive than isolated words—they capture more between-listener variance (Mueller, 2001; Taylor, 2003; Walden et al., 1983). However, much of this variance is due to factors outside the auditory periphery and even outside cognitive processes that are reasonably considered auditory. These factors pose even more significant problems when using sentence-based tests with individuals with more variation in cognitive ability, such as older individuals (Fraik & Bialystok, 2006; Peelle & Wingfield, 2016), children, or individuals with neurological or developmental disorders. These groups may have substantially more variance due to cognitive factors, and it may be challenging to isolate variance in performance to perceptual processes.

Additionally, there has been an increasing interest in examining difficult listening beyond intelligibility, by assessing how noise demands additional effort (Ohlenforst et al., 2017; Pichora-Fuller et al., 2016; Saramplis et al., 2009), or changes in the cortical network (Du et al., 2014; Kim et al., 2020; Wong et al., 2008; Bidelman et al., 2016). Sentence materials can make it difficult to isolate such differences to specifically auditory processes. For example, listeners may exert greater effort (e.g., greater pupil size in a pupillometry study) when attending to SiN;

however, it is not clear if listeners are allocating more effort to sentence processing, for example, rather than to auditory processes like streaming, grouping, selective attention, or speech perception.

Single-word tests—though currently somewhat less favored—may mitigate some of those issues. In contrast to sentence-based tests, typical single-word tests require listeners to repeat or choose single words. These are typically seen as less ecologically valid than sentence-based tests because they remove many extraneous individual differences underlying sentence-based tests. However, single-word tests afford some advantages.

First, because the selection of words is less constrained by plausibility factors, single word tests can sample the space of possible phonemes and coarticulatory contexts deliberately. As we describe shortly, the distribution of items could be chosen to match the frequency of those kinds of items (e.g., phonemes) in the world (maximizing predictive validity), or it could be done uniformly so that all phonemes are tested roughly equally (maximizing diagnostic strength). A uniform set of items, in particular, can potentially allow the clinician or researcher to isolate specific perceptual issues. For example, single-word tests can provide information about the discrimination of phonetic features, prosodic characteristics, and timing aspects of speech signals (Blarney et al., 1987; Geers & Brenner, 1994; Tyler et al., 1984).

Moreover, single words lessen memory demands and much of the complex cognitive operations associated with sentence processing, providing a potentially purer estimate of auditory or perceptual processing. This is not to say that single word tests have no cognitive demands. There are factors at the lexical (word) level that may impact single-word performance including word frequency (Elliott, Clifton, & Servi, 1983) and neighborhood density (e.g., Neighborhood Activation Model; Luce, 1986; Luce & Pisoni, 1998). The process of word recognition is a

complex cognitive process (e.g., Dahan & Magnuson, 2006 for a review). Nonetheless, all of these effects are present in sentence tests in addition to memory and sentence processing constraints. Thus, on balance, single word tests may do a better job isolating auditory from cognitive processes, using acoustically complex, real-world stimuli. This potentially may reduce the variability occurring exclusively as a result of non-auditory factors.

For research purposes, the use of single words allows more precise stimulus control and measurement of specific auditory factors involved in SiN perception (e.g., classes of phonemes, phonetic dimensions like voicing, consonants vs. vowels, etc.) as there is more freedom to select a representative distribution of sounds, and the simpler stimuli may allow the researcher to isolate the effect of a single contrast on performance. Critically, single word tests may also be more appropriate for temporally sensitive tools like magnetoencephalography (MEG), electroencephalography (EEG), pupillometry, and eye-tracking studies where fast-changing neural and physiological measures are time-locked to the stimulus.

B. Open vs. closed-set tests

The use of single word tests opens a second dimension on which SiN tests vary. In a typical testing scenario, clinicians and researchers can use either forced-choice (closed-set) or open-ended (open-set) tests. In the closed-set format, the listener receives a restricted list of words or letters to select from. One is correct; the other choices are foils. In an open-set format, listeners repeat back (or type) each word with no constraints imposed by the task. Here, the critical distinction is not so much the response modality (e.g., button-pushing vs. vocal) but whether the choices are constrained (closed set) or not (open).

There are several advantages to open-set tests. First, open-set tests are more difficult and avoid ceiling effects (even potentially at higher [easier] signal-to-noise ratios [SNRs]). Second,

open-set tests are not influenced by the response set. For example, in a closed set task, if a listener misheard a /b/ as an /m/, but the choices were /b/, /d/, and /g/, then /b/ may still be the closest match to their percept. As a result, they may choose the correct answer even though they misheard the speech. In this case, there is no way to measure the mistake. Thus, the difficulty of an item is shaped by the available choices. This can be problematic if response sets vary in difficulty across words (e.g., if all the labials are tested in easier sets than the fricatives). This can make it look like some sounds are more or less difficult, when the response sets are actually driving this. Finally, the lack of constraint in open-set tests may allow them to tap a wider range of factors that are known to influence speech processing such as talker variability and lexical competition (e.g., Clopper et al., 2006).

Despite these advantages, the open-set response format is not necessarily more ecologically valid than a closed- set task for three reasons. First, in everyday conversation, listeners map speech to meaning—they rarely need to repeat back what they hear. However, the neural pathways dedicated to mapping incoming speech to production are distinct from the pathways dedicated to meaning (e.g., Hickok & Poeppel, 2007). While open-set tests do not always involve speech production per se (some involve typing), all open set tests require listeners to map sound to its phonological, articulatory, or orthographic form. Consequently, open-set tests may not tap the pathways commonly used.

Second, and relatedly, open set responding brings in speech production processes. Here, speech production refers to a broader set of processes than just articulation, including selecting and retrieving a word from the lexicon and generating a complex motor response. If the goal is a pure assessment, this may just add variance and could even add to predictive validity. Like the issues raised for sentences, some of this variance may be due to processes that have nothing to do

with speech perception. Using a writing or typing task (instead of articulation) does not obviate the problem. Emerging work suggests that typing is subject to many of the same linguistic influences as word production and introduces more factors (sound/spelling regularity; Pinet et al., 2016).

Finally, the interaction of the cognitive processes involved in speech production with those involved in word recognition may impose more uncertainty on the measure. For example, the presence of lexical neighbors (e.g., words that differ by one phoneme) interferes with recognition (Luce, 1986; Luce & Pisoni, 1998), but facilitates speech production (e.g., Gordon, 2002; Middleton & Schwartz, 2010; Chen & Mirman, 2012). It is unclear how these forces may play out in special populations.

In the clinic, the fact that open-set tests rely on speech production may have other consequences. Open-set tests are harder to administer to participants with speech production deficits (e.g., Aphasia). They may also be problematic in children who can take 18 years to develop adult-like speech production (Sadagopan & Smith, 2008). In these groups, some open-set performance variation could be related to speech production, not SiN processing. Moreover, researchers are beginning to document that speech pathologists may struggle to identify children's productions in some cases (c.f., Munson et al., 2012), raising the issue of assessor reliability with individuals with disabilities or children.

The closed-set format overcomes some of these issues (even as it is subject to the concerns described above) as it does not require speech production. Moreover, the closed-set testing format is economical—tests can be rapidly administered and scored automatically without a human coder (Black, 1957), which is more efficient and can enable adaptive testing. Finally, by carefully choosing foils for each word, these assessments can pinpoint specific

perceptual difficulties at the feature- or phoneme-levels (Foster & Haggard, 1987). In the context of cognitive science and cognitive neuroscience, closed-set tests are highly advantageous as they minimize cognitive and cortical components due to speech production.

It is important to note here that closed-set tests do require a response (e.g., button presses or typing responses) which may make it harder for individuals from special populations. However, these responses (e.g., a button press or typing a response) are motorically simpler than speech production, and importantly, they are not inherently linguistic. This is important because individuals with a language or perception disorder are much more likely to face impairments in speech production than in button pressing. Moreover, inherently linguistic responses may be affected by many of the same linguistic factors that affect speech perception (e.g., neighborhood density) but in different ways. By using a simpler, non-linguistic response, these issues can be minimized (though not always avoided).

One common concern is that closed-set tests may not be sensitive to the same cognitive demands involved in everyday listening situations (e.g., Clopper et al., 2006; Sommers et al., 1997). Indeed, Sommers et al. (1997) found that performance in a closed-set SiN task was not affected by lexical competition (neighborhood density) or talker variability, whereas performance on an open-set task was. However, Clopper et al. (2006) showed that closed-set tests can better approximate speech perception by increasing response options (e.g., from 4 options to 6 options) and number of talkers. Thus, it is not clear whether these limits are because people don't engage these broader cognitive processes in closed-set tests, or they do engage these processes, but their influence is minimized by ceiling effects in some specific tests.

Even though single-word closed-set SiN tests are somewhat out of vogue, these tests have some advantages in that they can isolate auditory processes from many higher-level cognitive

processes (like sentence processing, speech production and short term memory); they can uniformly sample the phonetic space, and potentially isolate specific contrasts (e.g., voicing); they can be scored automatically and efficiently; and the timing properties can be controlled for in domains where timing precision is needed (i.e., cognitive neuroscience). Thus, The ITCP developed here uses the closed-set format.

One challenge in developing an ideal closed-set single-word task is identifying a set of response options for each word that effectively samples the possible responses a listener may consider but without biasing the subject. Some tests go so far as to use many possible responses and hold this consistent across trials (Clopper et al., 2006). This requires one to use orthographic (letter) stimuli – which may require a level of phonological awareness that can be problematic for children or people with brain damage. It may also interact in odd ways with the choice of stimuli. For example, if the target word was *fall*, the phonemes /v/ and /θ/ can be ruled out as *vall* and *thall* are not real words. Thus, while the use of all possible responses may appear to make this more of an open-set task, functionally speaking, it is not, and the functional number of reasonable foils may differ from word to word.

Alternatively, some closed-set tests may adopt a fixed number of foils and change the response options on each trial (e.g., CCT, Owens & Schubert, 1977). This approach allows the use of whole words as response options, reducing meta-phonological demands (while still requiring reading ability). When doing so, however, it may be challenging to control difficulty as the set of foils can be arbitrarily close (e.g., /b/ vs. /p/), far (/b/ vs. /f/), or may unintentionally stress certain phonological contrasts over others (e.g., if all the foils come from the same voicing or manner class). The ITCP attempts to mitigate this by controlling the target / foil relationships (e.g., the number of trials where there was a foil that contrasted by only one feature), by using a

computer-based search algorithm to find a set of targets and foils that constrain the range of difficulty, and with an IRT analysis to further refine this set.

C. Goals

With these issues in mind, our primary goal was to develop a single-word, closed-set task that attempts to solve many of the aforementioned issues. Our immediate motivation was to develop a task for cognitive neuroscience studies, where single-word tests allow for better control of stimuli and their timing, eliminates cortical processes related to speech production, and can better control the phonetic contrasts that are tested to ensure that we are roughly sampling the entire acoustic/phonetic space. However, the development and validation of this test was psychometrically oriented to enable this to be used across other studies and shared with other labs, and potentially to develop into a measure of clinical utility.

This paper serves two purposes. First, we describe the development and structure of the ITCP. Second, we present the results of our full validation experiment.

II. The Iowa Test of Consonant Perception (ITCP)

The ITCP was developed to improve upon typical closed-set SiN tests to provide a test of assessing consonant perception in noise using real words. We sought to address four limitations of typical single-word tests (both closed- and open-set) to create an assessment which as nearly as possible uniformly samples the space of possible phonemes and contexts.

First, in typical tests, it is common for words to be produced by a single talker (c.f., Torretta, 1995). This is problematic for three reasons. First, the use of a single talker eliminates one of the largest sources of acoustic variability present in everyday speech perception (McMurray and Jongman, 2011; Newman et al., 2001; Cole et al., 2010), where interaction with multiple talkers is typical (Clopper et al., 2006). Second, hearing loss and the use of

299 amplification devices can make some talkers more intelligible than others. For example, in a
300 bimodal cochlear implant (CI) configuration (a CI plus low-frequency acoustic hearing in the
301 contralateral ear), a listener may perform well with male talkers since the pitch is in range of the
302 acoustic ear, but struggle with female talkers whose pitch is in the electrical stimulation range.
303 Finally, from a measurement perspective, talkers vary in their intelligibility due to things like
304 dialect, articulatory precision, and rate. With a single talker, one may not achieve a robust,
305 generalizable measure of speech perception. Therefore, the ITCP uses four talkers (two female).

306 Second, single word tests allow the researcher to sample the acoustic phonetic space
307 deliberately. In this regard, there are two philosophies reflecting distinct goals. One can strive
308 for a representative sample by which the distribution of phonemes matches their frequency or
309 utility in the world (e.g., the CNC words; Lehiste & Peterson, 1959). This provides potentially
310 better predictive validity, but comes at the cost of diagnostic strength. Some phonemes may not
311 be sampled sufficiently to isolate the source of a listener's difficulty. Alternatively, one can
312 strive for uniformity by sampling all phonemes equally. This can help reveal the precise nature
313 of a hearing deficit but comes with a predictive validity cost. Both philosophies have utility, but
314 here we focused on uniformity, as we sought a test to help identify specific problems for both
315 clinical and basic research. Long term, future work should be able to develop weighted accuracy
316 measures (e.g., weight the frequency of each phoneme in the language) from this uniformly
317 sampled assessment (in the same way that the speech intelligibility index is computed from a
318 uniformly sampled audiogram). In contrast, converting a score from a representative (frequency
319 weighted) measure to a uniform one may not be possible.

320 Many existing single-word measures do not attempt to sample the space of consonants
321 and vowel spaces uniformly. For illustrative purposes, Figure 1 shows the distributions of onset

consonants tested (Figure 1) in two common tests, the CNC (an open-set task) and the CCT test (a closed-set task), along with similar measures for the ITCP. In these plots, the width of the arc illustrates the number of trials testing a specific onset phoneme. Open set tests such as the CNC can be scored based on all phonemes, and the CCT has foils to test both onset and coda consonants. But for comparison to the ITCP—which is designed to test primarily onset consonants—only onset consonants are considered for the CNC and CCT distributions. As Figure 1 shows, no single task is fully balanced: each misses several phonemes, but many are oversampled. The CNC test, for example, oversamples /w/ and under-samples /g/, /n/ and the non-sibilant fricatives; whereas the CCT dramatically under-samples /g/ and /d/ and misses several of the fricatives and sonorants altogether. This is not meant to critique these tests individually but to illustrate the differences in phoneme sampling.

Figure 1. (Color online). Distribution of consonants tested in two common tests and the ITCP (A. CNC; B. CCT; C. ITCP). Consonants are color coded by manner of articulation, and the width of each arc corresponds to the number of trials.

There are numerous reasons for this lack of a uniform distribution. There may be insufficient items in the language, or the test may focus only on phonemes that are the most frequently used. Consequently, results may not generalize to all English sounds; instead, such tests may capture largely stop consonant perception (for example). Thus, the ITCP samples most of the onset consonants of English and does so with an approximately equal number of trials for each phoneme and/or classes of phonemes (e.g., stops, fricatives, etc.; see Figure 1C).

Third, in any closed-set task, accuracy is not solely a function of the target sound—the available response options influence performance. For example, even if a listener cannot hear the difference between /b/ and /d/, they could still distinguish *beak*, *teak*, *peak*, and *leak* (since /d/ is not an option). Similarly, a test that always contrasted /b/ and /p/ (but never /b/ and /d/) is functionally a test of voicing discrimination, not speech perception writ large. Thus, it was crucial not only that the target sounds in the ITCP span the full phonetic space but also that the contrasts established by each set span the phonetic space as well.

To accomplish this, the ITCP uses four response choices on each trial (the target + three foils), which balances phonetic contrasts across items to the extent that an English word is available to serve as a foil. Heat maps in Figure 2 show the frequency (count) of target + foil contrasts for the ITCP¹. Four response options were chosen because (1) it allows each trial to tap multiple contrasts; and (2) it is difficult enough to avoid ceiling effects; and it is small enough to avoid overloading working memory. All four options are minimal pairs that only differ on the initial consonant, and at least one

¹ Not all contrasts are possible in English. It is not possible to contrast sonorants in voicing (there is no voiceless counterpart to /l/ and /m/ for example) and /ʃ/, /θ/, and /ð/, have virtually no minimal pairs for voicing. There are also no manner contrasts for /k/, /g/, /t/ and /ð/ as those places of articulation only appear in one manner class. This is highlighted in Figure 2 with red boxes

Figure 2. (Color online). Heat map showing the number of trials that test a specific minimal pair contrast for each phoneme. For example, a /b/ trial testing place would use either a /g/ or /d/ as a foil; a /z/ trial testing voicing would have /s/ for a foil, and a /z/ trial testing manner would have /n/, /d/, /l/ and /ɹ/ for foils. Note that some contrasts (indicated in white with red boxes) are not possible in word-initial positions in English (sonorants cannot contrast voicing, and some places of articulation are found only in fricatives) or were so rare that no minimal pairs could be formed. Also note that we did not attempt to collapse neighboring places of articulation that are commonly treated similarly (e.g., /k/ [velar] and /ʃ/ [post-alveolar]) are treated as a 2-feature contrast [place + manner]; thus many two-feature changes are actually quite close in acoustic or articulatory space.

space of English words (Schwalje, Choi & McMurray, in prep; described shortly) to identify a set of items in which the foils—as much as possible—uniformly sampled the space of possible contrasts, and are as close as possible to expressing a single feature (place, voicing, and manner) contrast. This automated procedure was intended to reduce variation in difficulty across items that were due to the specific foil choices.

Finally, few speech perception tests systematically consider the role of coarticulation – the degree to which neighboring sounds influence each other. This is widely seen as a core source of acoustic ambiguity for normal hearing listeners as a /b/, for example, can be

dramatically different depending on the neighboring vowels (Delattre et al., 1955; McMurray & Jongman, 2011). Ignoring coarticulation may create two problems. First, the ability to compensate for coarticulation may be fundamental for good speech perception (McMurray & Jongman, 2011). Second, coarticulation can shape the frequency profile in ways that could be confounded with performance. Lip rounding (from an /u/, for example) lowers the preceding consonant spectrum (Daniloff & Moll, 1968). If /g/, for example, is only tested in a /u/ context but a /d/ is tested in an /i/ context, a listener who struggles with low-frequency sounds (e.g., a standard CI user) may appear to perform worse on velars than coronals when the difference in coarticulatory contexts is actually driving this. Thus, it is essential to test sounds in a range of contexts. However, as Figure 3 shows, this is not commonly considered by existing tests (panels A and B) and consequently many vowel contexts are dramatically under or over sampled.

The ITCP overcomes this by testing each consonant with four vowels that roughly span the quadrants of the vowel space, where maximal coarticulation would be exerted (see Figure 3 for the distribution of trials as a function of vowel context and Figure 4 for the co-occurrence of consonants with each of four vowel types). This was motivated by our goal of uniformity (permitting better diagnosticity) rather than representativeness (some CV pairs are more likely than others). Non-corner vowels were excluded to minimize the number of trials and because we could adequately sample the dimensions of frontness, and height from the corners.

Finally, we constrained the items in the ITCP to be real English words. This was done to ensure applicability to older adults, children, and people with brain damage (many of which are elderly) who may struggle with non-words, and to avoid lexical biases if a mix of words and nonwords were used (c.f., Coady & Evans, 2008; Glosser et al., 1997; Rogalsky,

Figure 3. (Color online). Distribution of vowels by type in two common speech tests and the ITCP (A. CNC; B. CCT; C. ITCP). Vowels are color coded by manner of articulation, and the width of each arc corresponds to the number of trials.

2015). As a result of this constraint, and the constraint that all four words in a set needed to be close minimal pairs, there were surprisingly few words available, and there were simply not

Figure 4. (Color online). Consonant by vowel-type cooccurrence counts for the 120 items in the ITCP. Color intensity represents magnitude with lighter colors representing a fewer number of trials testing a particular contrast within a phoneme and darker colors representing a greater number of trials testing a particular contrast within a phoneme.

enough words in English to use a given set only once (since a set would use up four words – the target and three foils, which would never even be heard).

Instead, the ITCP cycles through each of the four words in a set, and sets can then be used multiple times with a different target word. While repetition is not generally a good design feature, we took several steps to minimize learning effects. First, by cycling through each of the four items in a set, all words are equally likely. Thus, seeing the set *van/than/fan/man* does not prime the listener to expect a specific target word. Second, cycling through a whole set does raise the possibility of a “process of elimination” strategy. For example, after a *van* trial and a *fan* trial, subjects can rule those two words out on subsequent trials with that set. To avoid this, each word is heard at least twice (in some cases, the researcher might want to add several randomly selected repeat trials to make sure of this). Third, no word appears in multiple sets. Fourth, to mitigate the potential for participants to memorize the “exemplars” (the specific idiosyncratic acoustic

properties of a given recording), each word is only heard once by a given talker. Fifth, the task is fully randomized, which prevents participants from building up expectations about words they have heard or not heard. Finally, each item in a set of four is heard an equal number of times (excluding any repeat trials that were added). This lessens the influence of frequency and neighborhood effects by counterbalancing item-specific factors (e.g., *than* is more frequent than *van* in English, thus subjects may be more accurate for this item; however, by also testing them on their perception of *van* and averaging the results we can factor out frequency).

The ITCP tried to simultaneously satisfy all these constraints: the use of real words, relative uniform testing of each consonant, relatively balanced difficulty expressed in the foils, and an even distribution of coarticulatory contests. However, given the constraints of English, it could not be perfect. Sometimes, there were insufficient words available to ensure minimal close pairs, or the constraints of testing in sets of four items disrupted uniformity. For example, a set like *ban*, *man*, *van*, and *than* tests several manner-of articulation contrasts, for places of articulation near the front of the mouth (labials, labiodentals and dentals). However, it is missing the sonorant, /w/. To test /w/, we would have to add another set (*wall*, *ball*, *fall*, and *shawl*), but that adds an extra labial, sacrificing uniform sampling of the consonants, and it adds a less-close contrast (e.g., /w/ vs. /f/). Thus, the ITCP (and likely any similar test) cannot perfectly live up to the goals here. To maximize our satisfaction of these constraints, we exhaustively searched a million possible sets to find a reasonable set of sets. We then used an item-response-theory approach to constrain items further.

All raw and summary data, analysis code, and materials related to the ITCP are available on our OSF website (<https://osf.io/hycdu/>). In this repository, we provide a list of the words with the corresponding response options; sound files for the words recorded by four talkers in silence

and noise; a MATLAB script that can be used to add multi-talker babble at a specified level; and item difficulty estimates for each word which were measured in the study described below. We note that the item database is coarsely coded by broad phonological categories (place, manner and voicing), and in many cases we took liberties to avoid an overly fine-grained scheme that would make it harder to generalize across sets. We do not intend this as a rigorous analysis of the phonology of these words and it is provided for convenience of the users; more detail is available in the “Design_Read_Me.docx” located here: <https://osf.io/7cf6k/>.

Our goal with the repository is that a user should be able to build smaller or larger versions of the ITCP with any form of noise they want. In the repository, we also provide a document describing the design principles of the ITCP to ensure that the resulting design is appropriately balanced, and a table of the specific designs implemented here. We do not provide a specific testing script. The one used here was developed in the online platform, *Gorilla* (and can be viewed online at <https://gorilla.sc/openmaterials/97811>). This task should be simple enough to implement in any existing experimental control platform. Those wishing to stay within the Gorilla platform can simply clone our ITCP task using the link above.

A. ITCP Development and Construction

To create the ITCP, we used an iterative design process. First, we identified a large array of possible sets (words plus foils) that could be pared down into a list of sets that met the design principles (nearly uniform sampling, equal sampling across vowels, balanced difficulty based on the foils). Second, we recorded all words, and conducted a pilot study in the lab. Third, following pilot work, an Item Response Theory (IRT) analysis estimated the easiness of each item (word) in order to identify outliers. Finally, we constructed the final set of items, discarding items that were outliers in terms of easiness, but keeping phonetic balance in mind (e.g., a uniform

distribution of phonemes and an equal balance of contrasts in the foils).

1. Item development

Item sets used monosyllabic words that ended in a consonant or cluster (CVC, and in a few cases, CVCC words). Closed syllables (rather than CVs) were used because the final consonant allowed additional vowels (e.g., /ɪ/ and /æ/ are not permissible in an open syllable), giving more available words. We then used an automated procedure to sift through about a million possible sets of items, seeking sets that balanced the constraints outlined above.

We started by developing a comprehensive list of candidate words by pooling items from the Clearpond (Marian et al., 2012), MRC (Wilson, 1988), and IPHOD (Vaden et al., 2010) corpora. We used words with a frequency greater than 0.5 per 1,000,000 according to the SUBTLEX-US database (Brysbaert & New, 2009) and words with high neighborhood density—we discarded words with fewer than three near neighbors, as they could not form a set. At this stage, any word that appeared in the corpora meeting the prespecified constraints was included. These were hand-checked to ensure uniform phonemic transcriptions (across the corpora) and to cull any words that were not reasonably well known. This process led to a master set of candidates that was independent of the specific corpora.

Next, we constructed a series of sets of four words. Each set contained a target and three foils (though the foils would also serve as targets on other trials). Sets were chosen pseudo-randomly (using criteria described below) and were chosen without replacement so that words could not appear in more than one set. The algorithm used to choose sets attempted to respect the following goals, in order of priority: 1) The set of sets should comprehensively sample the possible initial consonants (and be roughly uniformly distributed). 2) Each consonant should appear with vowels from four broad classes (frontness × height). For this factor, we attempted to

sample from all four quadrants of the vowel-space, but collapsed nearby vowels (e.g., /i/ and /ɪ/ were both treated as high-front). 3) Sets should maximize within-set phoneme confusion (e.g., include as many single-feature contrasts as possible, e.g., /t/ vs. /d/, but not /t/ vs. /m/).

For each set of sets, this was done until we ran out of words to create the set of sets. Finally, we evaluated the goodness of fit of each set of sets, balancing the three goals listed above. We created one million sets of sets in this fashion. The resulting versions were compared and, for pilot testing, the three best-fit arrays with the least overlap between their member sets were combined to form a candidate array of 48 sets comprising 191 words². We then piloted those 191 words with listeners across two sessions to determine the difficulty of each set, to further reduce the array size to the minimal sets needed for an adequate test (see Section 2.2).

2. Auditory materials

All words were recorded in Audacity (Audacity Team, 2012) using a Kay CSL 4300B analog to digital board with a Shure-WH30 microphone in a sound-attenuated room. All words were sampled at 44.1 kHz and 16-bit depth. Four speakers of midland American English (two male and two females ranging in age from 18-25 years) were instructed to speak all 191 words 2-3 times as clear as possible with and without the carrier phrase of “he said [word]”. The carrier phrase was used to help ensure uniform prosody and rate.

Raw recordings were first processed using Audacity’s Noise Reduction algorithm which estimates the spectrum of the ambient room noise and removes it from the entire raw sound file. A check was performed over high-quality headphones to ensure that Audacity’s Noise Reduction algorithm removed excess room noise without introducing distortions. All exemplars of the same

² At this stage, the same word might appear in two sets; this was done to give more flexibility in choosing the final sets, and the repetition was eliminated after piloting.

word (4-6 words per recording) were grouped together into a new WAV file, and then one token of each word was selected as a final version of the word. Exemplars were selected to have uniform prosody and duration, clear articulation, and be free of any artifacts (e.g., jaw clicks, etc.). Each word was cut at zero-crossings in the WAV file as close to the start and end of the word to isolate just the energy related to the single word. We then performed minor editing to remove any remaining jaw clicks, loud aspiration, and other artifacts.

Finally, the senior author reviewed each selected token to determine if the token was a good exemplar of that word, if another token should be selected, or if the word should be rerecorded altogether. Talkers came back for at least one additional session to record any words flagged for rerecording to follow the same methods listed above.

3. Noise

Target and multi-speaker babble were digitally mixed using a MATLAB script (see our OSF page) to create a series of WAV files with a dB SNR of -1.5. For each trial, an isolated 1.5 second-long multi-talker babble noise was played. Babble-noise excerpts were extracted from an original five-minute-long eight-talker babble noise from the Revised SPIN Test (a compact disc published by Auditec, Inc., St. Louis, Missouri). All excerpts had a relatively constant RMS level (within +/- 1dB), and a distinct excerpt was used for each word. There was no ramp-up or ramp-down used. Target word onsets were at a random position between 0.5 and 1.0 s, and noise continued for a fixed period of 1.5 seconds.

The ITCP OSF site contains the MATLAB script for adding noise. The script is fully customizable and can add any amount of noise with any temporal properties (e.g., the ramp, the duration before the target, etc.). The user should be aware that a specific SNR in dB is difficult to achieve automatically with real speech, and the dB SNR parameter is an estimate. True dB

SNR should be measured in the sound field where the test will be administered.

4. Loudness normalization

To limit variation in loudness, especially for controlling signal-to-noise ratio, all words were amplitude-normalized. Automatic loudness normalization is difficult for two reasons. First, perceived loudness is a function of frequency (Dawson et al., 2017) and phonemes necessarily vary in spectral composition (e.g., a sibilant fricative will have more high frequency energy than a nasal). Second, it can be hard to quantify absolute loudness with a time varying envelope.

Thus, we adopted a hybrid procedure implemented with custom MATLAB scripts using the Audio Toolbox (R2018b, MathWorks, MA, USA). As is typical, this starts with a single estimate of loudness for each file. Then the point-wise amplitude of each waveform is scaled by this estimate. For this single estimate, we started by identifying all the time points over which the amplitude was greater than 90% of the maximum for that word and used the RMS amplitude as the loudness. In practice, this meant scaling for each word was generally performed according to the amplitude of the vowel (according to the sonority hierarchy; Clements, 1990), the point that is most stable across words. This constraint ensured that quieter sections of the word (i.e., the closure between the vowel and the final consonant, a low amplitude obstruent) do not contribute to the loudness estimate used for normalization. We then scaled the amplitude of every point according to this value to achieve a uniform scaling in each sample. All WAV files were normalized in this way across talkers. Finally, after stimuli were normalized in this way, each token was reviewed by two members of the team (native English speakers) using high-quality headphones to identify individual words which were slightly louder or softer than the others within a talker. These had their total intensity increased or decreased by up to 10%.

B. Pilot Experiment 1

The 48 sets identified in our initial procedure were tested in a pilot experiment. Normal-hearing listeners ($N=30$) heard each stimulus once through headphones. On each trial, individuals saw a fixation cross for 500 ms and then listened to a word spoken by a single speaker in multi-speaker babble (-1.5 dB SNR), at a random interval between 500 ms and 1 s from the onset. The entire duration of the babble was 1.5 s. Immediately after the offset of the babble, there was 1 s of silence. Following this, participants selected the word they heard amongst the four alternatives specified by our procedure (see Figure 5 for a schematic).

Results were analyzed with a 1-parameter logistic (1-PL) random effects IRT model using the *glmer* package in R (Bates et al., 2015)³. The IRT was used to identify outlier items (i.e., items that were easier or harder than expected). This 1-PL model included random intercepts of participant and item, and we used the estimated item intercept for each word as a measure of its easiness/difficulty. The model also included fixed effects of 1) talker; 2) place, voicing, and manner of the consonants; 3) vowel context; and 4) a limited set of interaction terms (these were coded similarly to the analysis employed here in the validation study and described in Section 4.3). The fixed effects tried to capture much of the known variance across phonemes (e.g., that non-sibilant fricatives are generally more difficult than sibilants). As a result, each word's estimated item intercepts can be interpreted as the difficulty or easiness of an item given its phoneme class, vowel, and talker. An intercept of 0 means that the item is no harder or easier than other similar items, where an intercept greater than 0 means it is easier than expected. This fixed + random effects scheme was used because we knew in advance that certain phonemes (e.g., non-sibilant fricatives like /f/ and /θ/) would be harder than others (stops) and our goal was

³ This is functionally equivalent to a logistic mixed effects model.

Figure 5. (Color online). Trial structure of the ITCP.

to ensure a uniform distribution of phonemes in the assessment (e.g., we did not want to exclude all the non-sibilants, just those that were harder than non-sibilants should be in general).

We then used these item difficulty estimates from this model to eliminate sets that contained outliers (items with extreme positive or negative difficulty estimates greater than +2 or less than -2). Note that the fixed effects of this model did not include any information about the difficulty expressed by the contrasts of the foils. Consequently, the easiness estimates likely reflect in part variation due to the foils (e.g., a word with all multi-feature foils would appear as easier than a word with single-feature foils). Thus, trimming out the extreme values helped constrain the overall easiness (driven in part by the foils) to be similar across items.

The IRT analysis produced a set of 120 words (split into 30 sets) which simultaneously balanced several factors: 1) roughly equal number of words for each consonant; 2) roughly equal distribution of vowel contexts, by manner and place of articulation; 3) no item could appear in more than one set; 4) sets maximized single-feature contrasts and were of roughly equal

difficulty (e.g., the number of one-or-two feature contrasts) across different phonemes. Given English language constraints, there is no perfect set that maximizes all of these constraints; however, our goal was to come close. If a researcher seeks to use a subset of items or to recombine them, we strongly urge them to respect these factors to ensure a uniform test.

C. Final ITCP

The final version of ITCP consisted of 120⁴ CVC words, each produced by two male and two female speakers of midland American English. The words spanned 19 onset consonants (i.e., /b/, /p/, /d/, /t/, /g/, /k/, /v/, /f/, /ð/, /θ/, /z/, /s/, /ʃ/, /m/, /n/, /l/, /ɹ/, /w/, /j/)⁵ and 8 vowels (i.e., /i/, /ɪ/, /e/, /æ/, /ɑ/, /ɔ/, /ʊ/, /u/). Vowels were grouped into four classes (high-front, high-back, low-front, low-back), where class contains one or more nearby vowels (e.g., /æ/ and /ɛ/ were both low-front). Within each phoneme × vowel combination, there is an average of 2 words, and most phonemes appear with vowels in each of the four quadrants (Figure 4). The ITCP includes four talkers, though each participant here was tested on only two; in practice, the ITCP could be expanded by using three or even all four talkers or reduced by using a single talker⁶. Consequently, the ITCP can range from 120 – 480 trials. Details about the number of trials

⁴ In the validation *latch* was used as a foil in lieu of *thatch* for the targets *batch* and *match*).

⁵ Four consonants were left out (e.g., /ʒ/, /h/, /tʃ/, /dʒ/). /ʒ/ was excluded due to the small number of items available that contrast this phoneme word initially. /h/ was left out because the initial development of the ITCP was for use in ERP experiments and it is too low amplitude and too variable to elicit reliable ERPs (though it should have been added back in when our goals were broadened). Finally, the two affricates (/tʃ/, /dʒ/) were left out because many phonological analyses treat these as two phonemes—not one—and our long-term goal was to be able to measure performance on isolated dimensions.

⁶ Though we note that a single talker may create “process of elimination” task demands. We discuss these (and how to potentially get around them) in the “design principles” document on the OSF site.

tapping specific phonological dimensions (e.g., voicing) are shown in Figure 2; and the number of trials for each vowel context are shown in Figure 4. The distribution of possible target-foil pairs is included in Appendix A, along with a confusion matrix (Appendix B) highlighting the probability of an error given the target phoneme across all participants in Session 1.

1. Pilot Experiment 2

To ensure performance was not due to differences in stimulus audibility, we ran a second pilot study ($N = 45$) assessing performance on the final items in quiet. This was run online using the Gorilla platform (gorilla.sc; Anwyl-Irvine et al., 2019) and the Prolific (prolific.co) recruitment platform. Methods were identical to those used in the validation study below (except for the absence of noise). Participants were reimbursed for their time.

The mean level of performance in silence (proportion correct) across all speakers and items was near ceiling ($M = .95$, $SD = .08$, range = .49 – 1.00). The mean level of performance (proportion correct) across all items was also high ($M = .95$, $SD = .05$, range .73 - 1.00). The mean performance between speakers was also high: F1 ($M = .94$, $SD = .23$); F2 ($M = .96$, $SD = .19$), M1 ($M = .96$, $SD = .18$), M2 ($M = .94$, $SD = .24$).

III. Validation Study

A. Overview

The empirical study reported here is a validation of the complete assessment. We tested normal-hearing listeners to establish the reliability and validity of the ITCP and gather estimates of item-level easiness. We assessed convergent validity by relating the ITCP to two other speech measures (tested in noise): CNC (a single word open-set task) and AzBio (an open-set sentence-based task; Spahr et al., 2012). Both the CNC and AzBio are widely used clinically with hearing-

impaired populations (e.g., The Minimum Speech Test Battery for Adult Cochlear Implant Users [MSTB], Luxford, 2011) as measures of speech perception ability. Further, the CNC and AzBio tests are both used by the University of Iowa Cochlear Implant research team (with which the ITCP will be used as part of a long-running research program). These validation measures allow the ITCP to be mapped to current clinical measures and could help unify research and clinical assessments.

All participants completed the ITCP, the CNC words (100 items), and the AzBio (1 list of 20 sentences). To assess test-retest reliability, we examined ITCP performance in a smaller group of listeners across two sessions spaced one week apart. Data collection took place online using Gorilla (Anwyl-Irvine et al., 2019). While online testing offers some specific advantages worth noting, the advantages and limitations will be discussed before turning to the methods.

1. Online testing

In recent years, many labs have begun to explore online platforms to build and run experiments. In the lab, collecting data can be time-consuming and expensive and tedious. However, online data collection poses several challenges for auditory work. Although web technologies can effectively standardize the presentation of simple visual stimuli (such as words or images), researchers have significantly less control over the quality and loudness of audio stimuli and, historically, the precision of the onset time of the stimulus. In-lab research typically entails a careful specification of the signal-to-noise ratio and the overall amplitude of stimuli. Stimuli are typically presented to all participants via the same high-quality headphones or speakers and in a sound-attenuating chamber with no visual distractions. For online studies, audio hardware varies among users, and it is almost impossible to ensure that auditory stimuli are

presented at a consistent volume across listeners⁷. Also, researchers have no control over the acoustic environment where the testing takes place; therefore, most participants will be listening in settings that are less neutral than a sound-attenuated booth.

Despite giving up experimental control in some areas, online auditory processing studies show high fidelity to lab-based studies. Cooke et al. (2011), for instance, found that laboratory and online participants were similarly affected by changes in signal-to-noise ratio and the type of masker noise (i.e., multi-talker babble, speech-shaped noise, etc.). In addition, Slote and Strand (2016) demonstrated a correlation between online and in-lab measures of both speech-in-noise identification (Experiment 1) and response times in an auditory lexical decision task (Experiment 2). Obtaining this kind of reliability requires techniques to ensure 1) that subjects are wearing headphones; 2) that the sound card is of sufficient quality; and 3) that the stimuli are audible.

With these solutions in hand, online testing may offer many advantages for a project like this. First, online data collection allows for more diverse participants than university participant pools, and these participants are willing to participate for less compensation as they can participate at the time and place of their choosing (Paolacci et al., 2010). Online data collection also allows researchers to recruit a large number of participants at a quicker rate than traditional laboratory settings—even during periods when recruiting undergraduates is difficult, such as between terms (Crump et al., 2013; Grootswager, 2020; Mason & Suri, 2011). A larger and more diverse group of participants can increase between-subject variance, which helps correlational studies like this one and leads to a more generalizable sample.

Second, given that online users never interact with an experimenter and have no

⁷ Although their ability to adjust the volume may make it such that online users are better matched at a subjective level of loudness (e.g., the level at which they feel like they can perform the task accurately) even if they are not matched objectively.

preconceptions about the kinds of studies being done in a particular research lab, online data collection may help avoid experimenter bias or effects of participant expectation.

Finally, and most importantly, online listeners' diverse listening situations may be a strength for this study. The goal of this study is not to estimate a psychophysical threshold but to ask how variation in performance in the ITCP relates to variation in other tests and to itself. In this context, diverse listening situations may yield a better approximation of general confusability and intelligibility than do data obtained from stimuli presented in a carefully controlled setting. This is because the same issues driving diversity in listening conditions (e.g., sound quality, background environment) apply in the ITCP and the CNC/AzBio sessions. Thus, these results may generalize to a variety of sound presentation formats, overall amplitudes, and so forth, and as a result, the conclusions drawn from online experimentation may be more robust and generalizable to natural settings than lab-collected findings.

B. Methods

1. Participants

Three hundred and eighteen participants signed up online using the Gorilla hosting and experiment platform (gorilla.sc; Anwyl-Irvine et al., 2019). Participants were recruited via Prolific (prolific.co) and reimbursed for their time. Using pre-screening questionnaires on Prolific, we limited our sample to participants from the USA, aged between 18–47, and native English speakers. Participants were also screened to ensure they wore headphones during the task and had no history of self-reported neurological, visual, or auditory issues. After rejecting participants that did not pass the headphones screener ($n = 50$) and eliminating from analysis any individuals that did not complete all tests within a session ($n = 69$), the final sample size for Session 1 was 199 participants. Ninety-eight of these participants successfully returned to

complete Session 2. A sensitivity analysis indicated that this sample size ($n = 98$) provided adequate power (0.80) to detect a small effect size ($r = 0.28$) or larger. The demographic information for those that completed both sessions is shown in Table 1.

2. Materials

All tests were programmed using Gorilla and can be viewed at: <https://gorilla.sc/openmaterials/97811>. Audio files were converted to MP3 at 320 kb/s. The master copies (in WAV format) are available on the OSF site (<https://osf.io/hycdu/>).

- a. *Headphones screener*. The headphone screener is a six-trial task taken from Woods et al. (2017). On each trial, three tones of the same frequency and duration were

Table 1. Demographic Variables (N=97)

Factor	M / N (range / %)
Age	27 years (23, 35)
Gender	
Female	48 (49%)
Male	48 (49%)
Other	1 (1.0%)
Race	
Asian	9 (22%)
Black or African American	11 (27%)
White	21 (51%)
Unknown	56

1 participant did not complete the questionnaire.

presented sequentially. One tone had a lower amplitude than the other two tones.

Tones were presented in stereo, but the tones in the left and right channels were 180 degrees out of phase across stereo channels—in free field, these sounds should cancel out or create distortion, whereas they will be perfectly clear over headphones. The listener picked which of the three tones was the quietest. Performance is generally at the ceiling when wearing headphones, but poor when listening in the free field (due to phase cancellation).

- 701 *b. ITCP.* Each participant was randomized to one of four counterbalanced lists by the
702 experimental control software. Each list contained 240 trials⁸, with each word spoken
703 by one male and one female talker, with each list containing a different combination
704 of male and female talkers. For reliability testing, the second test for a given subject
705 used a list that tested the two talkers not used in Session 1. We used the same
706 procedure as in the pilot (Figure 5 for a schematic). A break was provided after each
707 block of 50 trials. Before the experiment proper, participants were given eight
708 practice trials, with feedback, to familiarize themselves with the task.
- 709 *c. CNC word recognition.* The CNC word recognition test (Lehiste & Peterson, 1959)
710 was used as a proximal validity measure. It consists of 500 test words organized into
711 50-word lists (10 lists in total) with a frequency-weighted consonant distribution. For
712 our validation study, we used Lists 1 and 4 for a total of 100 individual words.
- 713 Words were presented at -2.5 signal-to-noise ratio (dB SNR) in multi-talker
714 babble. On each trial, individuals saw a fixation cross for 500 ms and then heard a
715 word, spoken by a single male speaker in the same multi-speaker babble used in the
716 ITCP task. At the offset of the audio, participants typed the word they heard before
717 going on to the next screen. Breaks were provided every 50 trials. Words were
718 presented in a random order. Written responses were scored using the *lrd* package in
719 R (Maxwell et al., 2020). This package automates scoring of single-word responses.
720 Responses were correct if the typed response completely matched the target.
- 721 *d. AzBio sentence recognition.* The AzBio sentences were used to assess validity with a

⁸ We also had 10 extra trials that served to eliminate process of elimination bias. Specifically, we repeated *cell*, *chute*, *cook*, *gab*, *lock*, *lot*, *nab*, *rock*, *shore*, and *thong*.

more distal measure. It consists of 1000 sentences recorded from two male and two female talkers (Spahr et al., 2012). For our validation study, we presented AzBio List 1 (20 sentences, in random order)—at -2.0 dB SNR in multi-talker babble. On each trial, participants first saw a fixation cross for 500 ms and then heard a sentence, spoken by either a male or female talker in the same multi-speaker babble used in the ITCP and CNC tests. At the offset of the audio, participants typed the words in the sentence. Written responses were hand-scored by two independent reviewers. We employed a single-score, absolute agreement, two-way random effects model, and found high agreement among the two raters, $ICC(A,1) = .989$, 95% CI = [.988, .990]. As a result, only the scores from the first reviewer were used. During scoring, a trial was considered correct if all words in the sentence were correct. Individual words were correct if they were the same word as in the target sentence with exceptions made for contractions (e.g., typed response of “it’s” for actual words “it is”) and for misspellings with the same meaning (e.g., typed “pak” for “pack”).

- e. Demographics questionnaire.* Participants indicated their native language (if not English); gender; race; age; if they had ever been diagnosed with hearing loss, neurological disorder, or have vision problems; if they had trouble hearing a sample audio file (yes or no); and to report the brand of headphones used during the task.

3. General procedure

The current study was run across two sessions, seven days apart. In Session 1, participants completed (in order) the headphones screener, ITCP, and CNC. In Session 2, they completed (in order) the headphones screener, ITCP, AzBio, and the basic demographics questionnaire.

- a. Session 1.* Upon entering the study online, participants were given general

information about the study to decide whether they wished to participate. At this point, participants provided informed consent. After consenting, participants were presented with noise and told to adjust the volume until it was at a comfortable level. Next, participants were given the headphones screening test. Participants had two attempts to pass the headphones screener. If they did not pass on the second attempt, they were excluded from the experiment. If the participant passed the headphones screening, they next completed the ITCP followed by the CNC.

b. Session 2. Seven days later, the Gorilla platform sent email reminders to participants for the second session. After logging in, participants completed the headphones screener and were given two attempts to pass it. Participants were then presented with the ITCP with a different combination of male and female speakers than they had for Session 1. After completing the ITCP, participants completed the AzBio task. At the end of Session 2, participants took the demographics questionnaire.

IV. Results

Our analysis starts by reporting descriptive statistics for overall performance. Next, we conducted an item analysis to obtain raw difficulty/easiness estimates for reporting with these items. Following this, we conducted a similar analysis which accounted for known sources of accuracy differences (e.g., differences among consonants, talkers, vowel contexts, and foil composition). This was intended to both evaluate our materials by asking if accuracy was systematically affected by the expected factors, and to identify the difficulty/easiness of each item *relative to* these factors (for use in future iterations of the ITCP). Finally, we report validity (correlations against the other speech-in-noise measures) and test/retest reliability.

Overall ITCP performance

The mean performance (proportion correct) across session 1 ranged from .32 to .89 ($M = .73$, $SD = .08$) with similar difficulty for session 2 ($M = .74$, $SD = .10$; Range: .43 to .90).

A. Individual item analysis

The words in the ITCP were evaluated to assess the relative easiness/difficulty of the individual words contained in the test (see Appendix C for base easiness values). A multilevel 1-PL Rasch model was constructed (model formula in *glmer* [R] notation: $\text{accuracy} \sim (1|\text{Participant}) + (1|\text{item})$). The code for these analyses is available on our OSF page (<https://osf.io/yunhp/>). The analyses used all available data from session 1 ($n = 199$). Each item and its easiness score can be found on our OSF page here (<https://osf.io/n496k/>). The items and their characteristics can be used for secondary analyses or for counterbalancing new ITCP lists. Note that these easiness estimates do not account for systematic differences among talkers, phonemes, or contexts; thus, they reflect the easiness of entire classes of sounds (e.g., non-sibilants are harder than other consonants).

B. Participant and item level analysis

Next, we constructed a more complex version of the prior model, which included fixed effects that capture several known sources of variance in trial-by-trial performance: phonetic factors, coarticulatory contexts, differences among talkers, and foil composition. This model included random item-level and participant-level effects. The easiness values conditionalized on these factors are presented in Appendix C.

With this more complex model, we had two goals. First, by estimating the item-level random effects, we estimate the relative easiness/difficulty of the individual words *relative to the factors captured by the fixed effects*. Here, the fixed effects code for the systematic differences among phonemes (etc.), and the random effects capture the relative easiness after accounting for

791 this. Given this goal, the particular structure of the fixed effects matters less than whether or not
792 they capture differences among the phonemes, context, and foil composition. The resulting
793 easiness estimates assess the degree to which an item is as easy or difficult as expected for that
794 particular phoneme/talker/context. These are probably the most relevant easiness/difficulty
795 estimates to balance when using the ITCP items for other purposes.

796 Second, by evaluating the significance of the fixed effects, we asked if factors like target
797 voicing, vowel context, or foil composition affected performance. It is important to note that
798 with respect to this goal, these analyses are exploratory and do not represent all the factors that
799 could influence speech perception, nor do they capture a perfect phonological analysis of these
800 words. Rather in developing these models, our goal was to derive a reasonable model which
801 avoided collinearity, had a relatively small number of terms, and permitted some inferences
802 about systematic factors of interest.

803 We considered several possible coding schemes to capture between-phoneme differences.
804 Recall that our goal was to ask if a specific token was easier or harder than expected for that
805 phoneme class. That ruled out an acoustic scheme as these acoustic cues would need to be
806 measured from the specific tokens. There is a variety of phonological options, but many of these
807 are isomorphic to each other (meaning they would capture the same cross-phoneme variance),
808 thus we strove for simplicity. We considered a simplistic fixed effects scheme that simply
809 crosses factors like place of articulation and voicing. However, this is not statistically sound.
810 The phonology of English is not fully balanced in many ways -- there are no voiceless
811 approximant liquids, nasals, or glides; and the post-alveolar and interdental places of articulation
812 only appear in fricatives. Consequently, any set of fixed effects based on broad phonological
813 features will have a high degree of collinearity. A voicing contrast, for example would be highly

correlated with a manner contrast (since there are no voiceless sonorants). Such collinearity is a serious issue in fitting mixed-effects or regression models. Consequently, we designed a fixed-effects coding scheme that captured orthogonal contrasts where possible (e.g., place and voicing within stop consonants) while capturing other consonant differences in a way that would not be confounded. For example, the voicing contrast was only active (-1 or 1) for stops and fricatives and was set to 0 for sonorants.

Fixed effects included the following contrast codes (-1, 0, 1). Consonant voicing was coded as +1 for voiced, -1 for voiceless, and 0 for sonorants (since there are no voiceless phonemes at these manners). Manner of articulation was coded in two codes: stops (stop or not +/-1), fricatives (fricative or not, +/-1), with sonorants as a reference category. Place of articulation for stop consonants was coded with two contrasts: bilabial or not (+/-1), and velar or not (+/-1), with alveolar as a reference category, and set to 0 for fricatives and sonorants. Place of articulation within fricatives was coded similarly with three contrasts (labio-dentals, interdental and alveolars) with post-alveolars as a reference category and set to 0 for all other contrasts. The six sonorants were coded with five contrast codes. These were set to 0 for stops and fricatives. They were +1 if the trial tested one specific sonorant (e.g., /m/, /n/, /l/, /ɹ/, /j/; with /w/ held out as the reference category) and -1 if it did not (e.g., the /m/ contrast was set to +1 if the sound was an /m/, and -1 for /n, l, r, etc. and 0 otherwise). Note that the vectors of fixed effects were orthogonal across phonemes; consequently, they capture similar variance to a set of orthogonal dummy codes allowing us to focus on the relative easiness of each token.

In addition to coding these phonological factors, we included talker type (F1, F2, M1, M2), vowel type (high front, high back, low front, and low back) as categorical variables. Lastly, we controlled for the influence of foils on speech recognition by computing the number of foils

that differed only by voicing, manner, or place in each set (see Figure 2). The model formula is in (1), in notation of the *lmer* R package. When fitting the models, we used the Optimx optimizer. Statistics for the full model are presented in Table 2.

$$\begin{aligned} \text{correct} \sim & \sim \text{isStop} + \text{isFric} + \text{Voicing} + \\ & \text{labialstop} + \text{velarstop} + \\ & \text{labiodentalfric} + \text{interdentalfric} + \text{AlveolarFric} + \\ & \text{son1} + \text{son2} + \text{son3} + \text{son4} + \text{son5} + \\ & \text{talker} + \text{vowel} + \\ & \text{NumMannerFoils} + \text{NumVoicingFoils} + \text{NumPlaceFoils} \end{aligned} \quad (1)$$

Table 2. Model Summary for Full Model

Variable	χ^2	DF	<i>p</i>
IsStop	0.186	1	.666
IsFric	0.067	1	.796
Voicing	0.610	1	.435
Labialstop	10.235	1	0.001
Velarstop	2.712	1	0.100
Labiodentalfric	35.920	1	<.001
Interdentalfric	41.29	1	<.001
AlveolarFric	0.224	1	0.635
Sonorant1	0.005	1	0.946
Sonorant2	4.469	1	0.035
Sonorant3	0.228	1	0.635
Sonorant4	0.010	1	0.917
Sonorant5	1.69	1	0.193
Talker	106.73	3	<.001
Vowel	33.78	3	<.001
NumVoicingFoils	0.103	1	0.749
NumPlaceFoils	2.60	1	0.107
NumMannerFoils	1.06	1	0.303

The primary goal of this model was to assess item easiness (the random intercept of each item) relative to these fixed effects. However, as an exploratory goal, we evaluated the significance of the fixed effects to validate that the expected patterns of difficulty would be observed. Significance was assessed via likelihood ratio tests wherein the full model was compared to a

Figure 6. Raincloud plots (Allen et al., 2019) depicting results for Session 1. A. Raincloud plots for stops. B. Raincloud plots for fricatives. C. Raincloud plots for sonorants. Shown are by-participant accuracies (dots), medians and quartiles (box plots), grand means (red dots), and distributions of accuracy scores (half violin kernel density plots).

reduced model (with the effect of interest removed). This is similar to how a main effect in a traditional analysis of variance (ANOVA) would be interpreted. There is some debate about appropriate random effects structures for fixed effects (Barr et al., 2014; Seedorff et al., 2020). However, the complexity of the model prevented us from fitting random slopes of participants, so fixed effect evaluation should be treated as exploratory and anti-conservative.

We start by considering the item-level (phonetic features) of the words themselves. We found no overall effect of manner of articulation ($\chi^2(2) = 0.238, p = .888$); that is, there was no evidence stops, fricatives, and sonorants differed as a whole. There was also no reliable effect of voicing ($\chi^2(1) = 0.61, p = .434$) within the fricatives and stops.

However, place of articulation within stop consonants showed an overall significant

effect ($\chi^2(2) = 9.84, p = .007$; Figure 6). This was because bilabials ($\chi^2(1) = 10.24, p < .001$) were harder to recognize on average. Similarly, there was also an overall effect of place within fricatives ($\chi^2(3) = 57.36, p < .001$). This was because labiodentals ($\chi^2(1) = 35.92, p < .001$), and interdental ($\chi^2(1) = 41.29, p < .001$) were harder to recognize on average—this was quite expected given prior work (McMurray and Jongman, 2011). There was a significant effect of consonant type within the sonorants ($\chi^2(5) = 12.47, p = .029$). This was driven by /n/ relative to other sonorants, $\chi^2(1) = 4.47, p = .035$. The finding that /n/ sounds are more difficult maps onto some prior work on nasality and speech perception (e.g., Beddor & Krakow, 1999).

Next, we turn to the two context factors. The effect of Talker was significant (Figure 7; $\chi^2(3) = 106.19, p < .001$). Post-hoc comparisons (Tukey-adjusted) using *emmeans* (Version 1.5.0; Lenth, 2020) showed that target words spoken by F1 were less likely to be perceived correctly than target words produced by M1 ($OR = 0.74, SE = 0.05, z = -7.89, p < .001$), M2 ($OR = 0.72, SE = 0.03, z = -8.73, p < .001$), and F2 ($OR = 0.71, SE = 0.03, z = -8.04, p < .001$). All

Figure 7. (Color online). Raincloud plots (Allen et al., 2019) depicting proportion correct during Session 1 as a function of Talker. Shown are by-participant accuracies (dots), medians and quartiles (box plots), grand means (red dots), and distributions of accuracy scores (half violin kernel density plots).

other talker contrasts were not significant.

Vowel type (Figure 8) was also significant ($\chi^2(3) = 29.90, p < .001$). Post-hoc tests revealed consonants before low back vowels were harder to recognize than consonants before high back ($OR = 0.42, SE = 0.46, z = -4.88, p < .001$), high front ($OR = 0.41, SE = 0.43, z = -5.16, p < .001$), and low front vowels ($OR = 0.64, SE = 0.12, z = -2.45, p = .027$).

Lastly, the three foil contrasts did not affect perception of the target, $ps > .11$.

Figure 8. (Color online). Raincloud plots depicting proportion correct during Session 1 as a function of vowel quadrant. Shown are by-participant accuracies (dots), medians and quartiles (box plots), grand means (red dots), and distributions of accuracy scores (half violin kernel density plots).

C. Test-retest reliability

Finally, we turn to the most important goal of this project: establishing the reliability and validity of the ITCP. There was no overall accuracy difference between Sessions 1 and 2, $M_{diff} = -.002, t(97) = -0.319, SE = 0.008, p = .750$. This validates the efficacy of the design to prevent learning effects (the use of all four items in a set, the lack of repetition of individual exemplars, use of multiple repetitions to avoid process of elimination strategies).

Figure 9. (Color online). A) Scatter plot of proportion correct between Session 1 and Session 2 of the ITCP, along with distribution of the data (histograms). B) Scatter plot of proportion correct between Session 1 of the ITCP and AzBio, along with distribution of the data (histograms). C) Scatter plot of proportion correct between Session 1 of the ITCP and CNC, along with distribution of the data (histograms). D) Scatter plot of proportion correct between AzBio and CNC, along with distribution of the data (histograms). Plots were created with *ggstatsplot* (Patil, 2021).

We next considered test-retest reliability of the ITCP. A scatterplot of Session 1 scores and Session 2 scores can be seen in Figure 9a which shows a close relationship between performance on the two sessions. We computed a numerical estimate of reliability using the

intraclass correlation coefficient (ICC; Koo & Li, 2016), estimated using the *irr* R package (vers. 0.84.1; Gamer et al., 2019). ICC is widely used within psychometrics (see Matheson, 2018) which assesses absolute agreement between repeated measures (Session 1 and 2). It contrasts with the standard correlation which reflects only predictability. Ninety-eight participants completed the ITCP twice. We used an average-score, absolute agreement, two-way random effects model, and we found good agreement among average percent correct across the two sessions, $ICC(A,2) = .80$, $F(97, 97.2) = 4.89$, $p < .001$, 95% CI = [.70, .86]. See Figure 9a for the correlation between Sessions 1 and 2.

D. Convergent validity

Finally, we examined the relationship between performance on Session 1 of the ITCP and the AzBio (Figure 9B) and CNC (Figure 9C). Only listeners who completed all three measures were included in the analysis ($n = 98$). We used a robust correlation method, the percentage-bend correlation (Wilcox, 1994), which keeps outliers in the analysis but down weights them to provide a better balance between Type 1 error and power. The use of the percentage-bend correlation avoids researcher degrees of freedom in choosing a threshold for rejecting outliers. We found a positive correlation between AzBio and ITCP, $r_{pb} = .59$, 95% CI [.44, .70], $t(98) = 7.10$, $p < .001$, see Figure 9B⁹. We also found a positive correlation between CNC and ITCP, $r_{pb} = .54$, 95% CI [.38, .67], $t(98) = 6.56$, $p < .001$, see Figure 9C.

V. Discussion

The goals of this project were twofold. First, we sought to create a single word, closed-set task that could be used experimentally (with potential clinical utility down the road). Critically, this task should 1) use real English words; 2) uniformly sample most consonants of English; 3)

⁹ At the request of a reviewer, we also computed this correlation after scoring AzBio in terms of the average proportion of correct words. The correlation ($r_{pb}=.63$) was very similar to the sentence-based result.

control foils to ensure they played a minimal role in item-level performance and create opportunities for assessing performance along specific phonetic dimensions down the road; and 4) use words from a variety of talker and vowel/coarticulatory contexts to ensure robust generalizability. Second, we sought to validate the task to ensure it possessed good psychometric properties and showed the expected effects of phonetic and contextual factors.

A. Design of the ITCP

Our results support the first goal. The iterative development and final design of the ITCP achieved its goals of uniformity and sampling (Figures 1-4; Appendix A), and the item-level difficulty (both in absolute and relative terms) is available for finer-grained analysis.

Moreover, while the analysis of the experimentally manipulated factors showed few large differences among consonants, there were robust effects of both talker and vowel context. The effects of talker and vowel context supports the need for assessments that systematically sample consonants from different talkers and from different coarticulatory contexts, as intelligibility can vary markedly. For example, the difference between the highest ($M = .75$) and lowest ($M = .69$) performing talkers was approximately 6%; see Figure 7) and the difference between the highest ($M = .79$) and lowest ($M = .66$) performing vowel was approximately 13% (see Figure 8)—absolute differences whose sizes are quite meaningful in a closed set task.

While the effect of a talker is not unexpected due to factors like dialect, rate, or articulation quality (though we attempted to select uniformly intelligible talkers with a standard accent), the effect of vowel quadrant across context is less expected. It is well known that coarticulatory context can shift consonant boundaries (e.g., Mann & Repp, 1980). However, an overall effect on intelligibility across most (or all) consonants has been reported previously (e.g., Donaldson, & Kreft, 2006; McMurray & Jongman, 2011; Singh & Black, 1966; Wang & Bilger,

1973). We found that low vowels—particularly low back vowels (/ɑ/ and /ɔ/)—generally led to consonants with lower intelligibility than consonants before high vowels. This may have been because low vowels generally have higher first formants (closer to F2); this may have made it more difficult to separate the formants to use them as independent sources of information (e.g., for place of articulation), particularly when F2 was low (as in back vowels). Indeed, we observed consonants preceding low-back vowels (which have the highest F1 and the lowest F2) were harder than consonants preceding low-front vowels (with a high F1, but also a higher F2). However, future phonetic work should examine this more systematically to understand the source of these intelligibility differences.

As a whole, however, these intelligibility differences support the need for assessments of speech perception to test phonemes across multiple contexts (talker and coarticulatory) to ensure that they robustly generalize to the variety of contexts listeners will encounter in the real world.

Finally, we note that a critical concern in the development of the ITCP was balancing the difficulty of the foils across consonant classes – a critical concern about closed-set tests. Our analyses with the composition of the foils relative to the target did not have significant effects. This may be because variation in difficulty related to foil selection was minimized in two ways. First, our automated procedures strove to balance this by selecting a set of items whose foils were uniformly close. Second, after the first round of testing we used an IRT model to eliminate sets that showed unexpectedly high or low performance (which was likely to be impacted by the foils). This finding is encouraging as it suggests variation in performance across sounds in the ITCP is likely due to the target sound, not, its foils.

B. Validity

Moving on to our second goal, our validation results showed that the ITCP is a valid and

accurate task. First, the performance across phonemes were generally in accord with prior estimates from laboratory experiments. For example, in stop consonants bilabials showed lower intelligibility than others (e.g., Miller & Nicely, 1955). Within fricatives, we observed lower performance for non-sibilants than sibilants (e.g., McMurray & Jongman, 2011). Overall, the ITCP task appears to capture the kinds of patterns one would expect from lab-based studies.

We also obtained high test-retest reliability of the ITCP, suggesting that the task can be re-administered after a week and possibly longer. Critically, there was no difference in mean accuracy between the two sessions indicating that we were able to successfully prevent learning by 1) using all four items within a set; 2) not repeating individual acoustic tokens; and 3) repeating sets more than once (to avoid a process of elimination strategy). Following this, the ITCP can be used for longitudinal testing in the same subjects. In this case, though, it may be advisable to switch talkers as listeners can store and retain exemplars of words spoken in particular voices over several days (c.f., Nygaard et al., 1995; see also Goldinger, 1996).

Finally, the ITCP showed strong positive correlations with other speech tests presented in noise (i.e., CNC and AzBio). These tests were correlated with the ITCP at $r = .56$ (CNC) and $r = .59$ (AzBio). While not psychometrically adequate, these SiN tests should be contextualized in light of the ITCP's test/retest reliability estimates of $r = .80$. As test/retest reliability is the absolute highest correlation one could expect (a test should not be correlated with a completely different measure more than itself), these validity estimates are fairly impressive (particularly if the unknown reliability of the CNC and AzBio are taken into account). It is important to note that these correlations were high even though the CNC and AzBio are open-set, suggesting that the closed-set format did not suffer from ceiling effects (a concern with closed-set testing). Moreover, it was particularly impressive that the correlation was as large as it was ($r = .59$) with

the sentence level test (AzBio), which was intended as a more distal measure. This suggests that when properly designed, a closed-set word recognition test can give similar performance to the currently more in-vogue open-set sentence tests. Further validation is, however, needed.

Collectively, the findings provide positive evidence for the basic application of the ITCP in evaluating consonant perception in background noise.

C. Availability

We have made the materials for the ITCP freely available online, and we hope that other labs can use it as a standardized set of speech perception materials for a variety of research purposes. These materials can be recombined into smaller and larger tests. Still, we highly caution researchers who wish to do this to pay attention to several design principles which are essential for validity. This includes a uniform sampling of the space (e.g., roughly equal numbers of trials for each consonant $\times$ vowel context $\times$ talker), use of all items in each set of four (so that subjects assume that all four items are equally likely), and the use of at least two repetitions of each item (so that subjects do not adopt a process of elimination strategy). To create your own version of the ITCP, we created a design principles document posted with the materials (<https://osf.io/cyfpe/>). The easiest approach, however, is to use all the items with two or more talkers, which gives 240 trials (2 talkers), 360 trials (3 talkers), or 480 trials (4 talkers). Our team is happy to consult with others on the appropriate way to do this.

D. Limitations

The first limitation of this validation study is that the data were collected online. With the advancement of online behavioral research methods, it has become possible to test large samples of participants outside the laboratory with favorable results (e.g., Crump et al., 2013). However, for auditory testing, it becomes notoriously difficult to control important auditory factors (e.g.,

1011 sound quality) due to testing without an experimenter present in a contained environment with
1012 the proper audio equipment. The lack of control might call into question the validity of the
1013 current results.

1014 To partially mitigate some of these concerns, we took special precautions by including a
1015 headphones screener (Woods et al., 2017) and a simple hearing test at the beginning of the
1016 experiment to ensure participants could hear the stimuli and were wearing proper headphones. In
1017 addition, we asked participants to self-disclose their hearing status. These seemed to be adequate
1018 precautions. We observed high test-retest reliability and correlations with other well-established
1019 SiN measures. Moreover, online testing may be a strength for this study by generalizing over a
1020 wider range of possible listening conditions. Despite this, it is premature to argue that these data
1021 support the immediate use of ITCP. Future testing should be conducted to establish normative
1022 data and compare our online validation study results to the gold standard of laboratory testing.
1023 Initial evidence from an in-lab study pilot that showed similar results to those observed here.

1024 A second limitation of this validation study is its reliance entirely on normal hearing
1025 participants. We will eventually test a more heterogeneous population such as younger listeners,
1026 hearing impaired listeners, and hearing aid users with the ITCP. We will do so for two reasons.
1027 First, it is essential to show that these materials are equally valid and reliable for these users.
1028 Validity is perhaps the biggest concern as cochlear implants, hearing aids, and other devices can
1029 alter the spectral composition and fidelity of the input. Listeners who use these devices hear in a
1030 fundamentally different way than normal-hearing listeners, and it is essential to document that
1031 this validity and reliability extends to these conditions. Second, the pattern of easiness/difficulty
1032 across items may change in such listeners due to the same altered input. Thus, performance
1033 patterns across phonemes may not hold for such listeners. Third, it is crucial to collect normative

1034 data with such populations to determine “how good is good”; at what level of ITCP performance
1035 should one be concerned that a given hearing aid user or CI user is likely to encounter problems.
1036 These normative data could inform clinical decision-making, although we note that most speech-
1037 in-noise tests currently in use in the clinic do not have such norms available. Thus, further
1038 research will be necessary to assess the validity and reliability of these materials for these
1039 specific applications and populations.

1040 As we described in the introduction, the ITCP was built with the goals of uniformly
1041 sampling the phonetic space and orthogonally varying phonetic properties along with contextual
1042 factors like articulatory context and vowels. At least from first principles, these goals suggest
1043 the ITCP should have been best suited for diagnosing and understanding specific areas of
1044 difficulty (or success) rather than predicting real-world outcomes. This may differ from
1045 assessments like the CNC, which for example, attempts to match the frequency of testing a
1046 phoneme to its frequency of use (though see Martin, Champlin et al., 2000 for discussion of the
1047 difficulty of this). Nonetheless, the fact that we found strong correlations with CNC (and AzBio)
1048 suggests these fundamental differences in design principles may not result in huge differences.
1049 In light of these design goals, an important area for future work will be developing and
1050 validating sub-score measures for particular subclasses of sounds (e.g., fricatives) or particular
1051 contrasts (voicings). It may also be useful to incorporate some form of frequency weighting
1052 scheme into the scoring structure for greater predictive validity based on an individual’s
1053 circumstances. Given the distribution of items and foils, this should be feasible with the present
1054 materials.

1055 The last limitation of the ITCP is that it is not a perfect assessment. That is, we tried our
1056 best to create a representative assessment that emulated real world situations by using multiple

speakers, uniformly sampling phonemic features, and balancing difficulty. In some instances, we were not successful due to the messy characteristics of the English language. Quite simply, all initial word consonants cannot exist in every category when dealing with real words (see Footnote 3). In other instances, we were clearly to blame (e.g., the lack of /h/). One concern is that the ITCP is not completely uniform. One solution to this problem might be to remove individual trials (e.g., an extra /b/ or /p/ trial) to achieve uniformity. We also note that the use of random effects models for assessment (De Boeck, 2008) could help. These models are structured similarly to our analysis (Equation 1). However, the goal is to estimate the random intercept of participants, which estimates each listeners latent ability, accounting for the fixed effects (e.g., talker, phoneme and item-level variance). These models are good at dealing with unbalanced designs and this helps them estimate individual participants' own ability level after accounting for an imbalance in the distribution of trials. Critically, this approach can also estimate participant ability relative to fixed effects such as consonant or talker – much like we used for the item analyses, potentially providing a robust estimate of subject ability.

While the ITCP is not perfect, it accomplishes several goals not addressed by other measures. First, it improves upon some currently available closed-set tests by attempting to uniformly sample the phonemic space and balance difficulty of the foils. Second, it is completely open—all of the materials and data are available for public use. This open science approach is not widely adopted in the hearing sciences, but we hope it will enable other researchers to use this assessment and improve upon it.

E. Conclusions

A plethora of standardized measures exists to study speech perception. While the field has gradually emphasized sentence over word measures and open-set of over closed-set tests,

there is a need for closed-set single word tests. As we have described, these can isolate word recognition from more general sentence processing and memory processes; they can more uniformly sample the phonetic space and the range of phonetic and other contexts; they offer more precise timing for time-locking to cognitive neuroscience, pupillometry and eye-tracking measures; and a closed-set task can eliminate challenges involving speech production and is easier to code. As we've described, existing measures often fail to uniformly capture the space; they do not fully sample coarticulatory contexts and talkers, and they do not systematically control the nature of the foils to minimize the role of the response options.

The ITCP is a single-word, closed-set task that uniformly samples the most frequently used isolated consonants and which uses response choices with equal proportions of phonetic features. This balance means that intelligibility estimates of the ITCP truly reflect virtually the entire set of word-initial isolated consonants in English, potentially enabling more diagnostic assessments of specific areas of difficulty. Our data show clear evidence of both validity and reliability. To facilitate the use of the ITCP (as well as conform to current open science practices), we have made all materials (audio files and scripts) along with important item characteristics freely and publicly available at our OSF page (<https://osf.io/hycdu/>). It is our hope that this will allow researchers to adopt and adapt the ITCP to fit their research needs.

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Appendix A

Figure 10. Number of trials on which a given target consonant was presented with a corresponding foil consonant.

Note. In the validation *latch* was used as a foil in lieu of *thatch* for the targets *batch* and *match*) so there are some asymmetries (e.g., b-l = 2, but l-b = 1).

Appendix B

Figure 11. Confusion matrix showing response accuracy given a target phoneme.

Appendix C

Figure 12. Easiness Plots for ITCP Items.

Note. Base model with no factors included (left panel). B. Conditionalized model with all factors included (right panel). Each dot represents an item and the numerical values represents the items corresponding set number. Positive estimates refer to how easy an item is; negative estimates refer to how difficult an item is.

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Tables

Table 1. Demographic Variables (N=97)

Factor	M / N (range / %)
Age	27 years (23, 35)
Gender	
Female	48 (49%)
Male	48 (49%)
Other	1 (1.0%)
Race	
Asian	9 (22%)
Black or African	11 (27%)
American	
White	21 (51%)
Unknown	56

1 participant did not complete the questionnaire.

Table 2. Model Summary for Full Model

Variable	χ^2	DF	<i>p</i>
isStop	0.186	1	0.666
isFric	0.067	1	0.796
Voicing	0.610	1	0.435
labialstop	10.235	1	0.001
velarstop	2.712	1	0.100
labiodentalfric	35.920	1	<.001
interdentalfric	41.29	1	<.001
Alveolorfric	0.224	1	0.635
Sonorant1	0.005	1	0.946
Sonorant2	4.469	1	0.035
Sonorant3	0.228	1	0.633
Sonorant4	0.010	1	0.917
Sonorant5	1.69	1	0.193
Talker	106.73	3	<.001
Vowel	33.78	3	<.001
NumVoicingFoils	0.103	1	0.749
NumPlaceFoils	2.60	1	0.107
NumMannerFoils	1.06	1	0.303

Figure Captions

Figure 1. (Color online). Distribution of consonants tested in two common speech tests and the ITCP (A. CNC; B. CCT; C. ITCP). Consonants are color coded by manner of articulation, and the width of each arc corresponds to the number of trials.

Figure 2. (Color online). Heat map showing the number of trials that test a specific minimal pair contrast for each phoneme. For example, a /b/ trial testing place would use either a /g/ or /d/ as a foil; a /z/ trial testing voicing would have /s/ for a foil, and a /z/ trial testing manner would have /n/, /d/, /l/ and /ɹ/ for foils. Note that some contrasts (indicated in white with red boxes) are not possible in word-initial position in English (sonorants cannot contrast voicing, and some places of articulation are found only in fricatives) or were so rare that no minimal pairs could be found. Also note that we did not attempt to collapse neighboring places of articulation that are commonly treated similarly (e.g., /k/ [velar] and /ʃ/ [post-alveolar]) are treated as a 2-feature contrast [place + manner]); thus many two features changes are actually quite close in acoustic or articulatory space.

Figure 3. (Color online). Distribution of vowels by type in two common speech tests and the ITCP (A. CNC; B. CCT; C. ITCP). Vowels are color coded by manner of articulation, and the width of each arc corresponds to the number of trials.

Figure 4. (Color online). Consonant by vowel-type cooccurrence counts for the 120 items in the ITCP. Color intensity represents magnitude with lighter colors representing a fewer number of trials testing a particular contrast within a phoneme and darker colors representing a greater number of trials testing a particular contrast within a phoneme.

Figure 5. (Color online). Trial structure of the ITCP.

Figure 6. Raincloud plots (Allen et al., 2019) depicting results for Session 1 as a function of place of articulation (separate plots) within each manner of articulation (separate panels). Shown are by-participant accuracies (dots), medians and quartiles (box plots), grand means (red dots), and distributions of accuracy scores (half violin kernel density plots).

Figure 7. (Color online). Raincloud plots (Allen et al., 2019) depicting proportion correct during Session 1 as a function of Talker. Shown are by-participant accuracies (dots), medians and quartiles (box plots), grand means (red dots), and distributions of accuracy scores (half violin kernel density plots).

Figure 8. (Color online). Raincloud plots depicting proportion correct during Session 1 as a function of vowel quadrant. Shown are by-participant accuracies (dots), medians and quartiles (box plots), grand means (red dots), and distributions of accuracy scores (half violin kernel density plots).

Figure 9. (Color online). A) Scatter plot of proportion correct between Session 1 and Session 2 of the ITCP along with distribution of the data (histograms) B) Scatter plot of proportion correct between Session 1 of the ITCP and AzBio along with distribution of the data (histograms). C) Scatter plot of proportion correct between Session 1 of the ITCP and CNC along with distribution of the data (histograms). D) Scatter plot of proportion correct between AzBio and CNC along with distribution of the data (histograms) Plots were created with *ggstatsplot* (Patil, 2021).

Figure 10 (color online). Number of trials on which a given target consonant was presented with a corresponding foil consonant.

Figure 11 (color online). Confusion matrix showing response accuracy given a target phoneme.

1512 Figure 12 (color online). Easiness plots for ITCP Items.

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