A Deep Neural Network Model of Audiovisual Speech Recognition Reports the McGurk Effect

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Abstract

In the McGurk effect, perception of an auditory syllable changes dramatically when it is paired with an incongruent visual syllable, countering our intuition that speech perception is solely an auditory process. The dominant modeling framework for the study of audiovisual speech perception is that of Bayesian causal inference, but current Bayesian models are unable to predict the wide range of percepts evoked by McGurk syllables. We explored whether a deep neural network known as AVHuBERT could provide an alternative modeling framework. AVHuBERT model variants were presented with syllables recorded from 8 different talkers. AVHuBERT identified the auditory syllable "ba" as "B" at a rate of 85%, but pairing with an incongruent visual “ga” reduced the "B" response rate to 41%, similar to the rate of 44% observed in 100 human participants presented with the same McGurk syllables. Other AVHuBERT responses to McGurk syllables also matched human percepts, including the canonical McGurk "fusion" percept of "da", responses without any initial consonant such as "ah" and responses with other initial consonants such as "fa". The ability to predict percepts experienced by humans but not predicted by current Bayesian models suggest that DNNs and Bayesian models may provide complementary windows into the perceptual mechanisms underlying human audiovisual speech perception.

Introduction

Humans perceive speech by integrating auditory and visual information from the face and voice of the talker. The powerful influence of visual information on speech perception is demonstrated by an illusion known as the McGurk effect, in which the pairing of incongruent auditory and visual syllables results in percepts other than the auditory syllable (McGurk & MacDonald, 1976). In the decades since its discovery, the McGurk effect has become a staple of psychology teaching and research, with the original paper cited nearly 10,000 times. However, mysteries remain about the perceptual processes underlying the McGurk effect.

Audiovisual speech perception, including the McGurk effect, is an example of multisensory integration, the process by which information from different sensory modalities are combined (Angelaki et al., 2009; Stein & Meredith, 1993). The dominant modeling framework for studying multisensory integration is termed *Bayesian causal inference* (Shams & Beierholm, 2022). The *Bayesian* aspect of the framework refers to the necessity of weighting the sensory cues by their reliability (Ernst & Banks, 2002), while *causal inference* refers to the necessity of estimating the likelihood that the cues arise from a single cause (Kording et al., 2007). Unlike simple audiovisual tasks, such as estimating the location of a paired beep and flash, applying Bayesian causal inference models to audiovisual speech perception is challenging because the input space (the physical characteristics of auditory and visual speech) and the output space of speech tokens do not have a simple relationship (Ma et al., 2009). This necessitates the construction of a representational space with a small number of speech tokens within which the integration computation can be performed (Aller & Noppeney, 2019; Ma et al., 2009; Magnotti & Beauchamp, 2015, 2017; Olasagasti & Giraud, 2020; Parise, 2024; Parise & Ernst, 2023).

For instance, in the McGurk effect, the pairing of visual “ga” with auditory “ba” may result in the percept of “da” (referred to as a "fusion" percept because it differs from the unisensory components) or the percept of "ba" (the auditory component of the McGurk stimulus) (Basu Mallick et al., 2015). A Bayesian causal inference model of the McGurk effect contains a representational space with only three syllables ("ba", "da" and "ga") organized so that "da" is intermediate between "ba" and "ga" (Magnotti & Beauchamp, 2015, 2017). Bayesian models have the advantage that every step is mathematically simple and easily interpretable. However, this interpretability comes at the cost of poor generalizability. In the real world, humans perceive thousands of different words, not just a handful of syllables.

An alternative approach is provided by deep neural networks (DNNs) trained for speech recognition. Rather than restricting output to a small set of predefined syllables, DNNs can transcribe arbitrary speech into complete words. This generalizability comes at the cost of reduced interpretability, as the purpose of the computations taking place in the dozens of layers and thousands of units in DNNs is opaque. The contrasting nature of Bayesian causal inference models (high interpretability/low generalizability) and DNNs (low interpretability/high generalizability) suggests that they could be complementary tools for studying audiovisual speech perception. A key test of models is their ability to predict human perception. Within the limits of their restricted representational space, Bayesian models predict human perception of McGurk syllables. However, it is unknown whether DNNs report the McGurk effect. To answer this question, we studied a DNN known as Audiovisual Hidden-unit Bidirectional Encoder Representations from Transformers. AVHuBERT takes as input both auditory and visual speech streams and transcribes audiovisual speech with a 1.4% word error rate, similar to human performance (Shi et al., 2022).

AVHuBERT was presented with McGurk stimuli recorded from 8 different talkers, as well as a variety of other congruent, incongruent, and unisensory syllables. The responses of AVHuBERT were compared with human participants presented with the same stimuli. In addition to the fusion percept of "da" and the auditory percept of "ba", humans report a variety of other percepts to McGurk syllables that are not predicted by current Bayesian models, including percepts of only a vowel without any initial consonant, such as "ah", and percepts with other initial consonants, such as "fa" (Basu Mallick et al., 2015). If AVHuBERT reproduces the full range of percepts reported by humans to McGurk syllables, including the fusion percept, the auditory percept, and percepts not predicted by Bayesian models, it would indicate potential similarity with human perceptual processes, warranting further investigation of DNNs as a modeling tool to complement Bayesian causal inference models. Conversely, a failure to report human-like responses would suggest that AVHuBERT is poorly suited as a model for human perception of the McGurk effect.

Methods

Speech stimuli

Stimuli were recorded from 8 different talkers (4 male and 4 female) and consisted of auditory and visual recordings of the syllables "ba", "ga" and "da". The recordings were presented in auditory-only format (Aba; Aga; Ada); visual-only format (Vba; Vga; Vda); and audiovisual format. The audiovisual stimuli consisted of congruent pairings (AbaVba; AgaVga; AdaVda) and two incongruent pairings, the McGurk pairing (AbaVga) and the inverse, non-McGurk pairing (AgaVba).

Response scoring

Speech stimuli were presented to AVHuBERT using the default processing pipeline described in the AVHuBERT documentation (*https://github.com/facebookresearch/av_hubert*). For each stimulus, AVHuBERT generated five response predictions and the likelihood of each one. Response likelihoods were converted to percentages so that the sum for each stimulus totaled 100%. The first phoneme of each response was classified as one of the phonemes in the Carnegie Mellon pronouncing dictionary (http://www.speech.cs.cmu.edu/cgi-bin/cmudict) as described in (Yu et al., 2024).

AVHuBERT responded to McGurk stimuli with 18 different phonemes. To simplify data presentation, these were grouped into 6 categories that together comprised 99% of responses to McGurk stimuli. The category of "responses without an initial consonant" consisted of "ah" and similar responses (classified as "AA" by the dictionary, 23% of responses), "huh" and similar responses (classified as "HH", 3%),"uh" and similar responses (classified as "AH", 1%), or "our" and similar responses (classified as "AW", 3%). The category of "fusion responses" consisted of the phonemes "TH" (13%), "D" (5%), "DH" (3%) and "T" (0%). "B" (41%), "F" (6%), "L" (0.8%) and "G" (0.3%) responses received their own category. See the supplementary online

material (SOM) for a complete list of raw responses, computed phoneme likelihoods, and analysis code.

AVHuBERT model and model variants

The original AVHuBERT-large model (Shi et al., 2022) was downloaded from GitHub (*https://github.com/facebookresearch/av_hubert*, fixed version archived to read-only on Sept 1, 2024) and installed on an Apple Mac Studio with 192 GB of RAM. The AVHuBERT architecture consists of four functional parts: separate auditory and visual feature extractors; 24 layers of transformer encoders that combine the auditory and visual features; and a sequence-to-sequence decoder that produces transcribed output in the form of text tokens.

To study the sensitivity of the AVHuBERT model, slight perturbations were introduced into the first six transformer layers (the model layers most important for integrating auditory and visual speech information). The perturbations were restricted to the linear output layer ("out_proj") of the transformer encoders (Vaswani et al., 2017). A normal distribution with mean of zero and standard deviation of 0.1 was used as the noise generator, resulting in only small changes to the model weights. One hundred unique random number seeds were used to create 100 model variants: this assured that each model variant contained different model weights, but that the variants could be uniquely identified and reproduced if necessary.

Significance calculations

To calculate statistical significance, t-tests were performed using *R*. See the supplementary online material (SOM) for full statistical results.

Comparison with human responses

For comparison with the AVHuBERT responses to McGurk stimuli, we reanalyzed data from 100 human participants collected for the open choice portion of Experiment 2 of Basu Mallick et al.

(2015). Identical McGurk stimuli were tested in humans and in AVHuBERT model variants, and the response scoring procedure described above was applied. The output of Bayesian causal inference models and human responses to AgaVba are from (Magnotti & Beauchamp, 2017).

Results

The hallmark of the McGurk effect is a change in the perception of auditory "ba" (Aba) when it is paired with an incongruent visual "ga" (AbaVga). AVHuBERT model variants were presented with Aba and AbaVga syllables recorded from 8 different talkers. Responses were sorted by their initial phoneme and grouped into 6 categories comprising 99% of AVHuBERT responses to McGurk AbaVga syllables.

Response rates changed dramatically when auditory "ba" was paired with incongruent visual "ga" (Figure 1A). The largest change was for the phoneme "B". The rate of "B" responses decreased by 45%, from 85.2% for Aba to 40.7% for AbaVga (means across talkers and model variants). This was balanced by large increases in the rate of responses containing phonemes with no initial consonant (from 9% for Aba to 30% for AbaVga, $p < 10^{-16}$ from paired *t*-test) and the rate of fusion responses (from 0% to 21%, $p < 10^{-16}$). Three low-frequency responses also increased, “F" (1% to 6%, $p < 10^{-16}$), "L" (0% to 0.8%, $p = 10^{-5}$) and "G" (0% to 0.3%, $p = 10^{-4}$).

The increase in "no initial consonant" and "fusion" responses were examined in more detail by examining responses to control stimuli. Responses with no initial consonant were found in 58% of responses to Vga (the visual component of the McGurk syllable) and 9% of responses to Aba (the auditory component), indicating that no-initial-consonant responses were not specific to McGurk syllables. In contrast, fusion responses were selectively enhanced, with significantly higher rates for McGurk syllables (21%) than Vga (6%) or Aba (0.2%); the incongruent pairing of AgaVba (0.1%); or the congruent pairings of AbaVba (0%) and AgaVga (0.3%; all $p < 10^{-16}$).

Comparisons with human perception

AVHuBERT responses to AbaVga McGurk syllables recorded from 8 different talkers contained 18 different initial phonemes When presented with the same stimuli, human

participants produced responses corresponding to 17 different phonemes. A Bayesian causal inference model produced only 3 different phonemes (Figure 2A).

This diversity of responses was specific to McGurk syllables. Responses were highly uniform for the congruent syllables AbaVba, AgaVga and AdaVda, with human participants and AVHuBERT variants producing identical responses (corresponding to the correct response) at a rate of 97% for humans and 94% for AVHuBERT (means across syllables, talkers and participants/variants).

The most frequent response to McGurk syllables for both humans and AVHuBERT was the "B" response, corresponding to the auditory component of the syllable (mean response rate of 44% *vs.* 41%, humans *vs.* AVHuBERT, $p = 0.3$ from unpaired *t*-test with unequal variance). There was high variability in the rate of "B" responses across 100 AVHuBERT model variants (range 15% to 62%) and even higher variability across 100 human participants (range 0% to 100%, Figure 2B).

Humans had more fusion responses than AVHuBERT (41% *vs.* 21%, $p = 10^{-8}$) and more "G" responses (6% *vs.* 0.3%, $p = 10^{-6}$) AVHuBERT had more responses with no initial consonant (30% *vs.* 3%, $p < 10^{-16}$) and more "F" responses (6% *vs.* 2%; $p = 10^{-4}$). Response rates for "L" were similar (1.3% human *vs.* 0.8% AVHuBERT, $p = 0.3$).

A final comparison examined responses to a syllable consisting of auditory "ga" paired with incongruent visual "ba", the inverse of the McGurk pairing. The AgaVba pairing produced mainly auditory-matching "G" responses in both humans (96%) and AVHuBERT variants (91%), unlike AbaVga McGurk syllables, which evoked fewer auditory-matching "B" responses (44%/41%).

Discussion

The signature of the McGurk effect is a change in perception of auditory "ba" when paired with an incongruent visual "ga". Dramatic changes in response rates were observed when AVHuBERT was presented with Aba and AbaVga syllables recorded from 8 different talkers, providing an affirmative answer to the question "Does AVHuBERT report the McGurk effect?"

A measure of the influence of visual speech is the rate of auditory-matching "B" responses to McGurk syllables, with lower rates indicating increasing visual influence. Humans and AVHuBERT showed equivalent rates of "B" responses. Humans presented with McGurk syllables reported a broad range of percepts, as did AVHuBERT, including the so-called fusion percept of “da” described in the original description of the effect (McGurk & MacDonald, 1976). Humans and AVHuBERT reports were also similar for an incongruent control syllable consisting of the reverse McGurk pairing of AgaVba, with both groups showing little visual influence.

The ability to predict human behavior is an important requirement for models, and the similarities between human responses and AVHuBERT suggest that it could be a useful tool for interrogating the perceptual processes underlying human audiovisual speech perception.

Bayesian Causal Inference models

AVHuBERT is not the only model capable of reproducing the McGurk effect. Most current models of the McGurk effect operate in the framework of Bayesian causal inference (Aller & Noppeney, 2019; Magnotti & Beauchamp, 2015, 2017; Olasagasti & Giraud, 2020; Parise, 2024; Parise & Ernst, 2023) making it worthwhile to compare the two types of models.

Bayesian causal inference models require explicit assumptions about the representational space used by humans during speech perception. The original description of the McGurk effect proposed an explanation grounded in perceptual processing: “da” is pronounced with an open mouth, compatible with the visual properties of “ga”, while in the auditory domain, the acoustics

of “da” are similar to “ba”. Thus, the fusion percept represents a compromise between conflicting sensory cues (McGurk & MacDonald, 1976). The CIMS (causal inference of multisensory speech) Bayesian model instantiates this idea by assuming a joint audiovisual representational space in which “da” is intermediate between “ba” and “ga”. The CIMS accurately models human perception of McGurk syllables and inverse McGurk syllables, such as AgaVba (Magnotti & Beauchamp, 2017).

Comparison of Bayesian Causal Inference models and DNNs

A useful way to compare Bayesian causal inference models with DNNs such as AVHuBERT are along the axes of generalizability and interpretability. Bayesian causal inference models generalize poorly. Bayesian models can only return the tokens in the representational space with which they are constructed, such as the three syllables in CIMS. To compare model predictions with human perception testing human participants with a forced choice experimental design in which the tokens in model space correspond to the forced choices. Human speech perception is not limited to a handful of syllables, but due to the high dimensional nature of audiovisual speech features, it may not be possible to create Bayesian models that can process more than a handful of syllables.

Unlike Bayesian models, DNNs such as AVHuBERT generalize well. By design, they can transcribe any auditory, visual or audiovisual speech and estimate the likelihood of the component words. The generalizability comes at the cost of interpretability. The model AVHuBERT has 325 million parameters to describe the dozens of layers in its DNN, making the computations performed within it difficult to discern (Shi et al., 2022). Conversely, Bayesian causal inference models contain only a few steps controlled by a handful of parameters. Each

computation is mathematically simple and can be understood conceptually as the weighted average of alternative percepts.

Differences with human perception

One way to think of the distribution of responses to McGurk AbaVga syllables is as either corresponding to the auditory component ("ba"), the visual component ("ga"), or the consensus fusion percept ("da"). For auditory-corresponding responses, the rate of "B" responses was equivalent between AVHuBERT and humans. AVHuBERT frequently classified the visual component presented on its own (Vga) as "no-initial-consonant" and there were many "no-initial-consonant" responses to McGurk syllables. These "no-initial-consonant" responses may therefore represent a visual-corresponding response for AVHuBERT, accounting for their significantly higher rate in AVHuBERT than humans. Conversely, human rates of "G" responses (corresponding to the true visual component) were significantly higher than the rate of "G" responses for AVHuBERT; human rates of fusion responses were also greater.

One relatively recent discovery about the McGurk effect is high individual variability, a finding that has been replicated across speakers of different native languages (Basu Mallick et al., 2015; Dong et al., 2025; Magnotti et al., 2024, 2025; Strand et al., 2014; Tiippana et al., 2023). As shown in Figure 2B, human participants span the entire range of visual influence, from 0% to 100%, despite having normal or corrected-to-normal vision. High individual variability has also been observed in other tasks involving audiovisual speech perception, such as the ability to comprehend audiovisual speech with high levels of auditory noise (Rennig et al., 2020; Van Engen et al., 2014).

The sources of variability are unclear, but may reflect the contribution of many factors, each of which has a small influence. The eye movements made by observers when viewing faces

account for a small but significant amount of variance, with observers who prefer to fixate the mouth of a talking face showing more visual influence for McGurk (Gurler et al., 2015) and noisy speech tasks (Rennig et al., 2020). Variations in unisensory speech perception (Dong et al., 2025) and lip reading ability (Strand et al., 2014) also account for variance in McGurk susceptibility.

In the present study, AVHuBERT model variants were constructed by adding small amounts of noise to the model connections in the DNN layers most important for audiovisual integration. This produced a four-fold variation in visual influence for McGurk syllables (15% to 62%) while retaining high accuracy for congruent audiovisual syllable.

To reach the variability observed across human participants (0% to 100%) one approach would be to retrain or fine-tune AVHuBERT with different speech material. Humans experience very different language environments during development and simulating this process by training DNN models with speech that varied in the number of audible and visible talkers, the number of talkers speaking at once, and the levels of background noise, would be expected to increase the variability across models.

Potential applications of DNN models of audiovisual speech perception

The architecture of DNNs was inspired by biological neural systems, and therefore there is a possible correspondence between them (*e.g.* model units ~ neurons, model weights ~ synaptic strengths). Examining the internal structure of AVHuBERT might give clues to the neural substrates of the McGurk effect, as has been successfully demonstrated for DNNs and convolutional neural networks (CNNs) trained to accomplish visual, auditory, and language tasks (Kell et al., 2018; Kumar et al., 2024; Li et al., 2023; Saddler & McDermott, 2024; Yamins et al., 2014; Yamins & DiCarlo, 2016). Of course, the many possible methodological confounds in

comparisons between DNN/CNNs and human brains warrant careful consideration (Dujmovic et al., 2024; Hadidi et al., 2025) and emphasize the diversity of possible neural network architectures (Rideaux et al., 2021).

In the perceptual domain, the ability of AVHuBERT to transcribe any speech stimulus means that it should be possible to test combinations of incongruent audiovisual speech that have never been presented to humans before, potentially leading to the discovery of previously unknown illusions related to the McGurk effect.

Figures

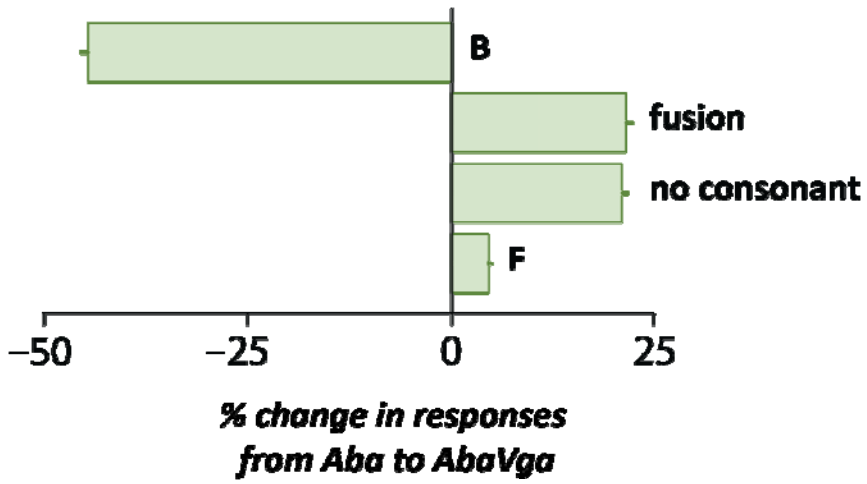

Figure 1

One hundred AVHuBERT model variants were presented with syllables recorded by 8 different talkers. The syllables consisted of auditory "ba" presented on its own (Aba) and the McGurk syllable pairing of auditory "ba" with visual "ga" (AbaVga). AVHuBERT responses were classified by their first phoneme into six categories, comprising 99% of all responses to McGurk stimuli. The rate of "B" responses decreased from Aba to AbaVga with a corresponding increase in the rate of other response categories. Bars for "G" (0.3%) and "L" (0.8%) responses not shown. Mean across talkers and variants, SEM across variants.

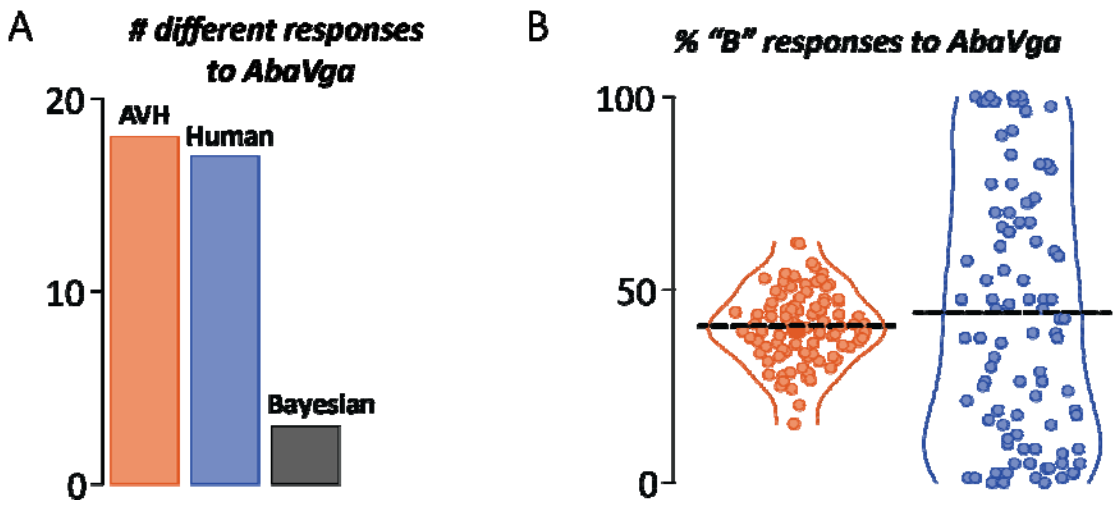

Figure 2

A. McGurk syllables (AbaVga) recorded from 8 different talkers were presented to 100 AVHuBERT model variants, 100 human participants, and a Bayesian causal inference model. The total number of different initial phonemes in the responses from each group were summed.

B. The rate of "B" responses to McGurk syllables for 100 AVHuBERT model variants (orange symbols; larger symbol near center of plot shows value for original AVHuBERT) and 100 human participants (blue symbols), one symbol per variant/participant (mean across 8 talkers for each variant/participant). Lower values indicate greater visual influence. Black dashed line shows mean across variants/participants. Horizontal spread of symbols and colored outline indicates probability density.

Declarations

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Ethics Approval. The study was approved by the University of Pennsylvania IRB.

Consent to participate. Informed consent was obtained from all participants included in the study.

Consent for publication. Participants gave written informed consent for publishing the overall results prior to the experiment.

Availability of data and materials. All data reported in this manuscript are included as supplemental material.

Code availability. All analysis code is included as supplemental material.

Open Practices Statement. All data and analysis code necessary to reproduce the results in this manuscript are included as supplemental material.

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