Mouthing off:
Effects of face masks on ASL perception and production

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Acknowledgements

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A note on anonymity

In cooperation with the Yale University IRB guidelines for Human Subject Research, all participants in this study were assured that their personal information and likenesses would be kept private, and that all recorded video data would be deleted upon publication. For that reason, the photographs in this thesis are representative “reenactments” of the phenomena I observed, rather than screenshots of the actual trials themselves. Maintaining anonymity is a unique challenge when doing sign language research, because unlike spoken languages, one must include images of all phenomena for the sake of clarity. Many sign language papers use line drawings showing generic, anonymous characters articulating the signs. This option was practically unavailable for this thesis, given the very large number of example sentences, time constraints, and my abject inability to draw human beings that don’t look like aliens.
Glossary of terms

Notational conventions

All glosses in this thesis use capital letters for American Sign Language (ASL) signs. For example, the sign meaning ‘paper’ is glossed as PAPER. This is an established trend in sign language linguistics literature. For signs that have a nonmanual component, I use a horizontal line that extends over the manual components that are coarticulated with the nonmanual marker. In the following gloss, the signer simultaneously raises their eyebrows (↑br) while signing BASEBALL, and nods their head (hn) while signing ME LIKE ‘I like’.

\[
\begin{array}{c c}
\text{↑br} & \text{hn} \\
\text{BASEBALL} & \text{ME LIKE} \\
\text{baseball-TOPIC 1SG like-AFF} \\
\text{‘I like baseball.’}
\end{array}
\]

Classifier glosses are formatted slightly differently for classified nouns vs. classified verbs. For classified nouns, the object is established before the classifier is introduced, in the format [CLASSIFIED OBJECT]–[CLASSIFIER TYPE]–[HANDSHAPE]. For example, ‘thin and curly moustache,’ which uses a DESCRIPTIVE CLASSIFIER (DCL) with a G-HANDSHAPE, is written MOUSTACHE-DCL-G. Classified verbs use the format [CLASSIFIER TYPE]–[HANDSHAPE]–[VERB]. For example, ‘two people walking along together,’ which uses a WHOLE-ENTITY CLASSIFIER (WECL) with a 2-HANDSHAPE, is written WECL-2:WALK.

Referential “indexing” is indicated with IX. After a signer introduces a referent, they can index that referent to a place in space by pointing. The signer can then use the spatial index to refer back to the referent at any later point in the discourse, without having to repeatedly sign the referent’s name or identity. For instance, a signer could introduce Josh by fingerspelling his name (fs-JOSH) and indexing him to the right side of the signing space (IX:RIGHT). From then on, pointing to the right can be taken to mean “Josh.”

Glossing abbreviations

1 first person (e.g. 1SG = first person singular, 1PL = first person plural, etc.)
2 second person
3 third person
AFF affirmative
ARC arc motion (used to index a plural referent)
BCL body classifier
↑br raised eyebrows
<table>
<thead>
<tr>
<th>Br</th>
<th>furrowed eyebrows</th>
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<tbody>
<tr>
<td>CL</td>
<td>classifier</td>
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<tr>
<td>DCL</td>
<td>descriptive classifier</td>
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<td>FUT</td>
<td>future tense</td>
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<tr>
<td>fs</td>
<td>fingerspelled</td>
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<tr>
<td>H1</td>
<td>dominant hand</td>
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<tr>
<td>H2</td>
<td>non-dominant hand</td>
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<tr>
<td>hn</td>
<td>head nod</td>
</tr>
<tr>
<td>hs</td>
<td>head shake</td>
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<tr>
<td>HS</td>
<td>handshape</td>
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<tr>
<td>ICL</td>
<td>instrumental classifier</td>
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<td>IF</td>
<td>inherent features</td>
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<td>IMG</td>
<td>inherent mouth gesture</td>
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<tr>
<td>IX</td>
<td>index</td>
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<td>MM</td>
<td>mouth morpheme</td>
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<td>NEG</td>
<td>negative</td>
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<td>NMM</td>
<td>nonmanual marker</td>
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<td>PAST</td>
<td>past tense</td>
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<td>PF</td>
<td>prosodic features</td>
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<tr>
<td>PL</td>
<td>plural</td>
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<tr>
<td>POA</td>
<td>place of articulation</td>
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<tr>
<td>POSS</td>
<td>possessive</td>
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<td>SG</td>
<td>singular</td>
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<td>SLM</td>
<td>spoken language mouthing</td>
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<td>TOPIC</td>
<td>topicalization</td>
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<td>Q</td>
<td>question/interrogative</td>
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<td>QAC</td>
<td>question-answer clause</td>
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<tr>
<td>WECL</td>
<td>whole-entity classifier</td>
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Abstract

This paper aims to determine the status of NONMANUAL MARKERS (NMMs) in the grammar of American Sign Language (ASL), particularly in terms of phonology, pragmatics, and perception. Despite the growing body of ASL linguistics literature and the ongoing development of models for sign language phonology, very little attention has been paid to the role of the mouth, eyebrows, and nonmanual body movements that accompany the manual dimension of signing. Given the unprecedented ubiquity of face masks due to the ongoing COVID-19 pandemic, I ask to what extent the obfuscation of the face affects sign perception and production for ASL signers. By forcibly blocking the mouth and observing the resulting linguistic changes, I investigate the importance and function of the face in a primarily manual language.

The study consists of a perception-production experiment featuring both non-Deaf and Deaf signers in masked and unmasked conditions. Participants performed perception and production tasks designed to target the activation of NMMs. Building upon existing morphophonological models of ASL, analyses of the perception-production loop are provided for three mouth movement types, each of which contribute uniquely to ASL grammatical structure and are affected differently by the presence of face masks.

SPOKEN LANGUAGE MOUTHINGS (SLMs) are mouth gestures that reflect the phonology of the spoken language that is most heavily in contact with the sign language (English, in this case). Differences in SLM usage between non-Deaf and Deaf participants suggest a bilingual-bimodal activation process in L2 signers. INHERENT MOUTH GESTURES (IMGs) are lexically-specified mouth movements which obligatorily co-occur with the manual components of certain signs. In minimal pairs that differ only in the presence or absence of an IMG, the sign without an IMG specification is shown to be the default interpretation when the mouth is blocked by a mask. This phenomenon is assumed to be the result of a pragmatic ANTI-HOMONYM constraint that defers to the sign with no IMG specification. Finally, MOUTH MORPHMES (MMs) carry adjectival and adverbial content, and intensify descriptions. These are shown to consist of more than just the mouth; redundant articulatory MM cues in the eyebrows and body are phonologized when the mouth is blocked, spreading to referent classifier signs and functioning as contrastive elements.

Face obfuscation presents a unique challenge for sign language communication, and consequentially reveals that each type of mouth movement plays an important role in ASL communication. Some mouth movements are encoded into the language’s phonology, while others mostly serve to aid in production. In this paper, the mouth is shown to be an essential articulator in a primarily manual language.

1 This experiment was funded $500 through the Saybrook College Mellon Senior Undergraduate Grant, and approved by the Yale Institutional Review Board for COVID-19 Human Subject Research.
The hands and the face

1.1 Introduction

In early 2020, the use of face masks became extremely widespread as a result of the COVID-19 pandemic. At the time of writing, mask mandates are still in effect across the United States. For those who use American Sign Language (ASL) as a first or second language, this has presented a unique and unprecedented communicative challenge. Deaf individuals, ASL interpreters, educators, and students have expressed frustration with the visual inaccessibility that hinders sign language use.

ASL requires coordinated movements of both the hands and face, “particularly including the eyes, eyebrows, and mouth,” and thus “requires the receiving communication partner to have unobstructed visual access” to the face (Guynes 2020). So-called “Deaf masks,” featuring a translucent window in the mouth area, have been developed in an attempt to rectify the communicative impairment that results from face obstruction. However, the full benefit of such a product is lost unless both the receiving and signing communication partners happen to be using them simultaneously (Elder 2020). Despite the problems that face masks have caused in Deaf and Hard-of-hearing communities, they have also highlighted the importance of NMMs, which are often neglected in the literature. The current study is thus motivated both by gaps in the theoretical literature, and by an ongoing, relevant, real-world problem that has intriguing linguistic implications.

The remainder of this chapter covers the basic structure of the sign in ASL. In section 1.2, I familiarize the reader with the ASL lexicon. Manual constructions (core lexicon signs, classifiers, and fingerspelled loanwords) are explained prior to nonmanual constructions. In section 1.3, I draw a distinction between manual and nonmanual information in the language by illustrating the five fundamental parameters that constitute each sign. Classifier constructions from the non-core lexicon are demonstrated in section 1.4, and fingerspelling is covered in section 1.5. After showing how the hands operate as primary articulators in the language, I explain the role of nonmanual articulators such as the head, eyebrows, body, and mouth. Section 1.6 introduces three distinct types of mouth movements – SPOKEN LANGUAGE MOUTHINGS, INHERENT MOUTH GESTURES, and MOUTH MORPHEMES – and their roles in the lexicon.
1.2 Structure of the lexicon

Adapting the framework presented in Brentari & Padden (2001) and Fenlon et al. (2017), I divide the ASL lexicon into native and non-native categories. The native lexicon is further divided into core and non-core signs, as shown below:

![Diagram of ASL lexicon]

**Figure 1.1: The ASL lexicon**

All signs in the core lexicon are manual. They are “comprised of sub-lexical units with a highly conventionalized form and meaning association,” and are the items listed in sign language dictionaries with citation forms (Fenlon et al. 2017: 454). Core signs are arbitrary and specific to their respective sign languages. The non-core lexicon is also entirely manual, and consists of classifier constructions that differ slightly from proper signs. Classifiers are discussed later in this chapter. These manual core and non-core signs are considered to be native elements, as they are specific and exclusive to ASL. Non-native forms, on the other hand, are borrowed from spoken languages. In ASL, non-native items are articulated by spelling out words as they would be written in English, using the ASL alphabet. This process, called fingerspelling, is further explained in section 1.5.

1.3 Manual vs. nonmanual information

Sign languages use the hands as primary instruments, unlike spoken languages which use the voice. However, not all information is carried in the hands. Words are represented by signs in ASL, and every sign uses at least one hand in some capacity. As with any language, though, full communication requires more than just the use of a single articulator. In the ORAL-AUDITORY spoken language modality, speakers make use of the face and hands to convey extralinguistic information that has no bearing on the language’s grammar. The VISUAL-SPATIAL modality of sign languages grants a more substantial grammatical role to the face. ASL incorporates a blend of manual and nonmanual information – that is, information carried by both the hands and by other parts of the body (Slobin 2006: 176). Nonmanual articulators function at all levels of linguistic structure, “from meaningless phonological components of lexical items to discourse markers” (Crasborn 2006: 669). Every sign language has nonmanual elements; it is difficult to even imagine a successful visual-spatial communication system that relies solely on the hands. This study concerns the grammatical status of three different types of mouth-based nonmanual markers, and investigates their
phonological and pragmatic functions by testing how ASL users react to the forced blocking of the face with surgical masks.

1.3.1 Parameters of the ASL sign

Each word in a spoken language like English is made up of a unique combination of individual sounds. Likewise, every ASL sign consists of five parameters with particular specifications (Bahan 1996: 12). These are generally defined as:

1. **HANDSHAPE**: The configuration of the hand(s) used in the sign
2. **PALM ORIENTATION**: The direction of the palm (e.g. inward, downward)
3. **MOVEMENT**: The specified movement path of the hands
4. **LOCATION**: The sign’s specified point(s) in space (e.g. chin, torso, forehead)
5. **NONMANUAL MARKERS**: Facial or body cues (e.g. raised eyebrows, mouth shapes)

In the same way that lexical items in spoken languages are composed of contrastive phonemes, so too are sign lexemes in ASL. For example, the sign BLONDE has the following parametric specifications:

1. **Y-HANDSHAPE**
2. **PALM ORIENTATION** facing downward
3. **MOVEMENT** of the dominant hand from the forehead to the back of the skull
4. **LOCATION** at the forehead
5. **No specified NONMANUAL MARKERS**

![Figure 1.2: BLONDE](image)

Each of the five ASL parameters have a large number of possible specifications; there are at least 50 distinct HANDSHAPES (and perhaps as many as 80) for lexemes in the core lexicon, i.e. the set of words with designated manual signs (Brentari 1998: 82-83). There is thus an enormous quantity of possible specification permutations for the five parameters.

Even the most complex models of sign language phonology and morphology tend to neglect NMMs, as “their role within phonological models [remains] unclear” (Brentari 1998: 462). Although every sign is overtly specified for a HANDSHAPE, PALM ORIENTATION, LOCATION, and MOVEMENT, most signs do not have a lexically-encoded NONMANUAL MARKER (NMM). Nonetheless, NMMs are certainly contrastive in the language; there is a small set of
minimal pairs which differ only in the presence or absence of a mouth movement. Additionally, eyebrow movements are used in ASL for syntactic functions including topicalization, indicating \textit{wh}- and \textit{yes/no} questions, and introducing \textsc{question-answer clauses} (QACs).

Models of sign language phonology have only recently begun to take shape. In the last 30 years, linguists have attempted to build a cohesive architecture to represent the possible parametric specifications using a “feature geometry” system that is strikingly similar to the Autosegmental Phonology model of spoken language features. Sandler (1989) and Brentari (1998) employ feature geometries in their Hand Tier and Prosodic models of ASL sign and syllable structure, respectively. These two models are elaborated upon in chapter 2. In a feature geometry, parameters are represented as a bundle of feature specifications, much like individual sounds in spoken languages. The highly-specific anatomical details for each parameter will not directly factor into any of the analyses presented in this paper, but they are assumed to be the underlying parametric structure moving forward. For example, \textsc{handshape} (HS) for \textsc{blonde} in Figure 1.2 should be interpreted as a shorthand for the specifications below:

![Figure 1.3: Autosegmental representation of BLONDE HS]

\subsection*{1.4 Classifiers}

As mentioned in the previous section, the \textit{non-core} category of the ASL lexicon consists of the constructions typically labeled \textsc{classifiers}. The grammatical status of these constructions has long been a subject of debate in ASL linguistics, but all analyses conclude that classifiers are specialized elements which are not signs \textit{per se} (Emmorey 2003). Instead, they indicate the semantic class of the signs to which they refer or “attach.” A full-fledged analysis of classifier constructions is beyond the scope of this study, but a basic knowledge of classifier typology is necessary in order to fully understand later chapters.

Classifiers have been described as both polymorphemic and as “blends of non-linguistic gesture and linguistic structures” because they permit a degree of iconicity and are not restricted to the same set of parametric specifications as proper signs (Supalla 1986; Liddell 2003). \textsc{handshape} is the only specified parameter for classifiers; signers are relatively free to map the specified hand configuration onto any number of \textsc{movements}, \textsc{palm orientations}, and \textsc{locations}, depending on what they would like to communicate. Sign
languages have the unique ability to pack a high level of morphological content and representational complexity into a very small number of movements or “syllables,” largely thanks to classifier constructions (Schick 1990). In the following subsections, I provide examples of the four major classifier categories defined in Morgan & Woll (2007: 1163).

1.4.1 Whole-entity classifiers (WECLs)

Classifiers in which the specified HANDSHAPE represents a previously-mentioned referent are commonly used in ASL discourse. Sometimes alternatively referred to as “semantic classifiers (SCLs),” the WECL category is comprised of a small set of HANDSHAPES with specific referential capacities. Generally, a signer will begin by introducing a referent with the citation form of a sign and (optionally) assigning it an indexed location in space. At any later point in the discourse, the signer can use the appropriate WECL to represent the referent and its real-world movement or location.

1) TWO BOY-IX BEST-FRIEND WECL-2:WALK
   two boy-3PL-TOPIC best-friends cl.walk-together
   ‘Two boys walked along together as best friends.’

In (1) above, the signer is free to use the WECL with the 2-HANDSHAPE again at any later time to represent the two boys walking side-by-side.

2) THIEF-WECL-3-LEFT POLICE-CAR-WECL-3-RIGHT WECL-3:DRIVE
   thief-cl.vehicle police-car-cl.vehicle cl.two-cars-chasing
   ‘The policeman pulled the thief over.’

---

2 In all glosses moving forward, the timing relation between manual signs and NMMs is represented by a horizontal line that extends across the NMM-specified section of the ASL phrase. This type of glossing draws loosely from the gestural score style of visualization, used to depict the temporal relationships between oral gestures in Articulatory Phonology (Browman & Goldstein 1989, 1992).
The two cars in (2) are indexed to the signer’s left and right hands using the 3-HANDSHAPE, designated for vehicles. In a single fluid, two-handed movement, denoted by WECL-3:DRIVE above, the signer can represent the thief driving in a swerving, fast path, with the police car gaining speed and finally pulling the thief to a stop. A large amount of information is stuffed into a single syllable in this case. Similarly, in (3) below, a simple tilt of the hand representing the lamp conveys its location and angled position on the table.

3) TABLE-WECL-FLAT LAMP-WECL-A-OPEN: TILTED
   table-CL.flat-surface lamp-CL.object-sitting-tilted
   ‘The lamp was sitting askew on the surface of the table.’

1.4.2 Instrumental classifiers (ICLs)

Signers can elaborate upon the manner of handling an object with INSTRUMENTAL CLASSIFIERS (ICLs). Typically, the selected HANDSHAPE for ICLs reflects the real-world shape of the object:

4) EVERY-MORNING COFFEE ME MAKE ICL-C: DRINK
   every-morning-TOPIC coffee 1SG make CL.drinking-from-cup
   ‘I make and drink a cup of coffee every morning.’

---

³ A detailed discussion of the ASL “syllable” is provided in the next chapter.
5) BALL GIRL:IX-RIGHT ICL-CLAW-5:THROW
ball-TOPIC girl- 3SG CL.throwing-spherical-object
‘The girl threw the ball.’

1.4.3 Descriptive classifiers (DCLs)

The class of DESCRIPTIVE CLASSIFIERS is fairly wide-ranging, and encompasses a large number of handshape configurations. These constructions are useful for specifying the size or shape of objects, people, designs, and so on:

6) MY FATHER HAVE MOUSTACHE-DCL-G
1SG-POSS father has moustache-CL.thin-curly
‘My dad’s moustache is thin and curly.’

DESCRIPTIVE CLASSIFIERS can also show the motion of the classical elements like fire, wind, or water, as in (8):

7) CANE ME NEED DCL-F
cane 1SG need-AFF CL.long-thin-AFF
‘I need a long, thin cane.’

DESCRIPTIVE CLASSIFIERS can also show the motion of the classical elements like fire, wind, or water, as in (8):

8) PIPE FINISH-BREAK WATER DCL-4
pipe PAST-break water CL.pouring
‘The pipe broke and water poured out everywhere.’
1.4.4 Body classifiers (BCLs)

Signers can iconically employ their own body to describe the behavior or appearance of another person, as in (9), where a signer physically yawns to depict the children doing the same:

9) CHILDREN BCL:YAWN WHY? CLASS BORING
   children CL.yawning why-Q class boring-AFF
   ‘The kids yawned because the class was so boring.’

It is worth noting that some teaching materials do not consider constructions like the one in (9) to be examples of classifiers, because the hands are not used for symbolic reference. Alternatively, signers can choose from a set of specified HANDSHAPES to represent particular body parts and their movements. In (10), the woman is first represented by a WECL with the 1-HANDSHAPE, and then her crossed legs are depicted with two crossed index fingers (BCL-1-1):

10) BENCH-WECL-2 WOMAN-WECL-1:WALK SIT BCL-1-1:CROSSED-LEGS
    bench-CL.flat-surface woman-CL.walking sit CL.crossing-legs
    ‘A woman sat down on the bench and crossed her legs.’

In (11) below, two BCLs are used. First, the upside-down V-HANDSHAPE depicts the waiter transitioning from a standing position to lying on the ground. Then, two V-HANDSHAPES become the collective eyes of the customers turning and staring at him:

11) WAITER-BCL-V:FALLING ALL-PEOPLE BCL-V:EYES
    waiter-CL.slipping-falling everyone CL.eyes-staring
    ‘Everyone turned and stared when the waiter slipped and fell.’

1.5 Fingerspelling

Words without a designated manual sign are commonly expressed with fingerspelling, a system of one-to-one mapping between HANDSHAPES and the letters of the English alphabet. Fingerspelling is also employed in free variation with manual signs, and can be used for
“hyperspecificity” or to avoid homonymy. To fingerspell a word, signers articulate the individual letters in succession. For example:

Skilled signers can fingerspell at very high speeds, given that native ASL users spell up to 15% of their overall lexical items (Morford & MacFarlane 2003; Padden & Gunsauls 2003). Sign languages tend to incorporate fingerspellings that reflect forms from the spoken languages that are most dominant in the same geographic region. In Uganda, for instance, where English is an official language, signers of Ugandan Sign Language (UgSL) use a high rate of fingerspelled English words. Individual sign languages develop their own manual alphabet, however, regardless of which orthography it reflects; fingerspelling in British Sign Language (BSL) reflects English orthography just like in ASL, but since the two languages are not related historically, the HANDSHAPES used for each letter are different.

1.6 A closer look at nonmanual markers

NONMANUAL MARKERS can manifest as mouth, eyebrow, and head movements, as well as any body movements that do not involve the hands. This paper primarily focuses on mouth and eyebrow movements as contrastive phonological segments, though head and body movements will also be discussed as redundant articulatory cues with which they naturally co-occur. In the following section, I lay the foundation for assigning contrastive status to mouth and eyebrow movements by discussing situations in which NMMs have already been shown to “have the same ability to carry lexical contrast” as the other sign parameters (Brentari 1992: 361).

1.6.1 The eyebrows and the body

In spoken language, the eyebrows and body are typically used for subtle extralinguistic or stylistic expression. The visual modality of sign languages permits a richer set of grammatical applications, such that eyebrow and body movements can carry both syntactic and prosodic information. Head movements, brow raising and furrowing, and modulation of the signing space are important for topicalization, conditionals, relative clauses, verb-noun agreement, and pronominalization (Pfau & Quer 2010; Zeshan 2004).

1.6.1.1 Head movements in negative constructions

All sign languages use NMMs for negation and affirmation to some degree, though not always contrastively (Puuponen et al. 2014: 48). Some languages – like Hong Kong Sign Language
(HKSL), Italian Sign Language (LIS), Jordanian Sign Language (LIU), and Indo-Pakistani Sign Language (IPSL) – require a manual negative particle in negative constructions. Co-occurring NMMs, such as headshakes or backward head tilting, are optional (Pfau & Quer 2010: 387). Conversely, manual particles are optional in ASL negative constructions; the co-occurring NONMANUAL MARKER alone can negate a proposition.

12)           hs      [                     hs]
   a. fs-MARY-IX:RIGHT NOT BRING DESSERT
      Mary-     3SG        NEG   bring-dessert-NEG

   b. fs-MARY-IX:RIGHT BRING DESSERT
      Mary-     3SG       bring-dessert-NEG
      ‘Mary didn’t bring dessert.’

In (12a), the overt manual sign NOT, in tandem with a negative headshake (hs), is sufficient to negate the following VP. The signer may also optionally spread the headshake over the VP [BRING DESSERT] (Pfau & Quer 2010: 389). Alternatively, the equivalent meaning may be expressed by omitting the negative particle NOT and obligatorily spreading the headshake over the VP, as in (12b). NMMs, therefore, can do the semantic work of certain manual particles in ASL.

1.6.1.2 Eyebrow movements in interrogatives

Eyebrow movements have a somewhat contrastive role in distinguishing between interrogative and affirmative clauses. The position of the eyebrows is obligatorily specified in all interrogative ASL constructions: they are raised [↑br] in yes/no questions, and furrowed [↓br] in wh-questions.

13)           ↑br  ↓br
   a. YOU SIGN ASL YOU  b. LANGUAGE YOU SIGN WHICH
      2SG  sign ASL 2SG-Q    language  2SG sign which-Q
      ‘Do you sign ASL?’     ‘Which languages do you sign?’
14) 

\[ \begin{align*} 
\text{a.} & \quad \text{PEOPLE-IX:ARC STARE-AT-ME} \\
& \quad \text{people- 3PL stare-at-me-Q} \\
& \quad \text{‘Are those people staring at me?’} \\
\text{b.} & \quad \text{PEOPLE-IX:ARC STARE-AT-ME WHY} \\
& \quad \text{people- 3PL stare-at-me why-Q} \\
& \quad \text{‘Why are those people staring at me?’} 
\end{align*} \]

ASL also has focused constructions that contain two parts; the first appears to be an interrogative clause, while the second “resembles a declarative clause answering that question” (Caponigro & Davidson 2011: 323). Truth-conditionally, these clauses – commonly referred to as QUESTION-ANSWER CLAUSES (QACs) – are equivalent to declarative constructions. The question element at the beginning of the QAC requires raised eyebrows, signaling that the signer is about to provide their own “answer” and is not expecting a response from the interlocutor. The “answer” is accompanied by an affirmative head nod (hn) and relaxation of the eyebrows.

15) 

\[ \begin{align*} 
\text{BABY-IX:RIGHT TIRED WHY? LAST-NIGHT IX:RIGHT SLEEP TIME-TWO} \\
& \quad \text{baby- 3SG tired why-Q last-night 3SG sleep-two-o’clock-AFF} \\
& \quad \text{‘The baby is tired because she went to sleep at 2:00 a.m. last night.’} \\
& \quad \text{(lit. ‘Why is the baby tired? Because she went to sleep at 2:00 a.m. last night.)} 
\end{align*} \]

16) 

\[ \begin{align*} 
\text{COLLEGE ME AFFORD HOW? MONEY BANK-IX:RIGHT LOAN-ME} \\
& \quad \text{college 1SG afford how-Q money bank- 3SG loan-me-AFF} \\
& \quad \text{‘I afford college by getting a loan from the bank.’} \\
& \quad \text{(lit. ‘How do I afford college? The bank loaned me money.’)} 
\end{align*} \]

Given the data above, we can see that there is a solid basis for assigning contrastive status to eyebrow movements in ASL. Though these examples demonstrate their syntactic function, in later chapters I will show that NMMs can also carry phonological contrast.

1.6.2 The mouth

Building on the typology in Brentari (1998) and Bickford & Fraychineaud (2008), I define three types of ASL mouth movements, each of which serve a different function:

1. SPOKEN LANGUAGE MOUTHINGS (SLMs), which are borrowed from English and reflect English phonology. These are the least contrastive mouth movements, as they are entirely optional and have no function in distinguishing meaning.
2. MOUTH MORPHEMES (MMs), which carry adverbial and adjectival content. These modify lexical information, but do not change core semantic properties of the sign.

3. INHERENT MOUTH GESTURES (IMGs), which are specified for lexical items, and create minimal pairs. These are the most contrastive mouth movements, as they distinguish meaning between words.

This study considers and tests all three types of mouth movements. SPOKEN LANGUAGE MOUTHINGS, INHERENT MOUTH GESTURES, and MOUTH MORPHEMES are discussed in greater detail in the following subsections.

1.6.2.1 SPOKEN LANGUAGE MOUTHINGS (SLMs)

SPOKEN LANGUAGE MOUTHINGS are a sort of “loan gesture” from spoken language. They are a crosslinguistic feature of sign languages, and reflect the phonology of the spoken lingua franca of the region in which a given sign language is used (Brentari & Padden 2001: 104). In the case of ASL, SLMs are “silent articulations of (a part of) a corresponding spoken word” from English, often the syllable that would be stressed in the word’s spoken form (Pfau & Quer 2010: 384). The rate of mouthing varies greatly among ASL signers; some people mouth nearly every word, others mouth only the most salient content in a phrase, and still others mouth almost no English words at all. Mouthing is particularly common among learners of the language who have had substantial spoken language input, but many Deaf signers also make extensive use of SLMs.

For the purposes of this study, I relate SLMs to fingerspelled loanwords, as both are examples of linguistic content that has been borrowed from English. Fingerspelled loanwords are manually-spelled English words, using the ASL alphabet. Some words do not have a designated manual sign and are always fingerspelled, though fingerspelling can also be used in free variation for words that do have a sign. Pfau & Quer (2010) argue that both SLMs and fingerspelled loanwords should be considered “language contact phenomena,” and do not constitute an integral part of the language outside of providing clarity and perhaps efficiency in communication; signers may mouth words in order to be obvious about which lexeme they mean to use, and they may choose to fingerspell signs rather than use the citation form of a sign for the purposes of avoiding ambiguity between two visually similar manual movements.

From this line of reasoning, I argue that SLMs are “loan gestures” that belong to the non-native lexicon. Since fingerspelled loans and SLMs both represent English words (orthographically on the one hand and phonologically on the other), and since they been argued to function as “tools for clarity and efficiency,” particularly among non-native signers, I start from the premise that they should be classified together as non-native elements (Fontana 2008).

1.6.2.2 MOUTH MORPHEMES (MMs)

Struxness (1996) provides a comprehensive list of 49 verb- and noun-modifying MOUTH MORPHEMES, though Bickford & Fraychineaud (2006) claim that only 17 are widely identified by signers. These morphemes carry adverbial and adjectival information, and they are
articulated simultaneously with the signs they modify. For example, one might modify the sign for DRIVE in the following ways, using the PRESSED and TH MOUTH MORPHEMES. In (17a)–(17c), “ICL” refers to the instrumental classifier that demonstrates the manner by which the signer claims to have operated the car:

17)   ↑br
a. CAR ME DRIVE ICL:STEERING
car-TOPIC 1SG drive ADV.steering
‘I drove a car.’

↑br
b. CAR ME DRIVE ICL:STEERING
 car-TOPIC 1SG drive-ADV.focused ADV.steering
 ‘I drove a car in a focused/concentrated way.’

↑br
TH
c. CAR ME DRIVE ICL:STEERING
 car-TOPIC 1SG drive-ADV.careless ADV.steering
 ‘I drove a car in a careless/sloppy way.’

In (a), DRIVE lacks an adverbial MOUTH MORPHEME, and the reading is neutral. In (b) and (c), DRIVE is modified by PRESSED and TH, respectively. The same process can occur with adjectival MMs, which modify nouns by co-occurring with the manual noun sign.

Some sources, e.g. Bickford & Fraychineaud (2006), suggest that the MOUTH MORPHEME may involve more than just the mouth, and that the eyebrows and corresponding body movements contribute to the adverbial and adjectival content. For example, in (17c) above, the TH morpheme is likely to co-occur with a relaxed or asymmetrical eyebrow position (to represent carelessness), and a sloppy or wobbly body movement. I am not aware of any pre-existing work that attempts to isolate the mouth movements of MMs to test whether the adjectival or adverbial effect is still perceived without any corresponding eyebrow or body cues. We will return to this question in the experimental section of the paper.

1.6.2.3 INHERENT MOUTH GESTURES (IMGS)

There is a small set of minimal pairs that differ only in the presence or absence of a mouth gesture. Unlike SLMs, these INHERENT MOUTH GESTURES are encoded into the phonology of the lexical item, and are thus obligatory for the correct articulation of the sign. The three universally attested IMGs and their respective minimal pairs are:

1. PAH [pa]: differentiates between FINALLY [+PAH] and SUCCESS [–PAH]
2. TH [θ]: differentiates between NOT-YET [+TH] and LATE [–TH]
3. SH [ʃ] and MUH [mʌ]: minimal triplet SHOULD [+SH], MUST [+MUH], and NEED [∅]
1.7 Summary

In this chapter, I introduced the parametric framework of the ASL sign, explained the distinction between manual and nonmanual information, and provided a typology of mouth movements. Parameter specifications like HANDSHAPE represent more complex bundles of feature specifications, which closely mirror the Autosegmental Phonology approach to spoken languages, using a branching structure that is further developed in the following chapter on the ASL syllable. Each of the three types of mouth movements have a distinct place in the ASL lexicon. SPOKEN LANGUAGE MOUTHINGS are non-contrastive and entirely optional, MOUTH MORPHEMES carry adjectival and adverbial information, and INHERENT MOUTH GESTURES are lexically-encoded contrastive segments. In the next chapter, I provide an overview of ASL syllable structure, address gaps in the ASL linguistics literature, and motivate my experimental study.
Background, existing morphophonological models, and motivation

ASL linguistics is relatively young, and the prototypical framework of syllable structure in the language is still up for debate. NONMANUAL MARKERS tend to be dismissed or left for further research in even the most rigorous models. However, with some expansion and alterations, the Hand-Tier Model (Sandler 1989) and Prosodic Model (Brentari 1998) are equipped to capture the mouth’s place alongside the hands within the structural hierarchy of the syllable. In this chapter, I delineate these two models as they stand, and argue in favor of filling the gaps for NONMANUAL MARKER research in the existing literature.

2.1 Models of ASL syllable structure

The earliest formal description of ASL phonology, proposed in Stokoe (1960), identified the tabula (place and setting); designator (hand configuration); and signation (internal and external hand movements) as the three salient “feature classes” that compose every sign. These feature classes are essentially a rephrasing (or perhaps, more accurately, a pre-phrasing) of the aforementioned sign parameters from section 1.3.1, except that they merge LOCATION and ORIENTATION into a single parameter, the tabula. NONMANUAL MARKERS were notably left out of this incipient model – a crucial flaw given the clear importance of the face in ASL grammar.

Similarly, the most influential post-Stokoe models of ASL phonology and syllable structure have carried on the trend of virtually overlooking NMMs. In the Move-Hold Model, proposed in Liddell (1984), signs are “segmented into Movements and Holds” that essentially reflect the property of sonority in spoken language; movements are analogous to vowels, and holds are analogous to consonants (Kubuğ 2008: 30). It is my personal view that the parallels between spoken and signed languages in the Move-Hold Model (and in the Hand-Tier Model, explained in the following section) are a little too heavy-handed and spoken-language-centric to properly capture what is really going on in sign languages. Nonetheless, established and familiar terms from spoken language linguistics provide an effective frame of reference that can easily be imposed onto the sign language modality as a starting point.
2.1.1 Hand-Tier Model

Sandler (1989) makes a conceptual connection between Movements and Locations with vowels and consonants, respectively. In this framework, syllables are broken down into two parametric components, LOCATIONS (L) and MOVEMENTS (M). The HANDSHAPE parameter, relabeled as HAND CONFIGURATION, has a specification which is linked to the L and M segments. Two syllabic structures are allowed: LML syllables, in which two LOCATIONS are linked to one another via a MOVEMENT; and L syllables, which involve no MOVEMENT. LML syllables are further divided into forms with and without a sign-internal HAND CONFIGURATION change (Sandler 2011: 7). The basic Hand-Tier Model schema, adapted from Kubuş (2008), is shown below:

![Hand-Tier Model Diagram](image)

**Figure 2.1:** Syllable structure in the Hand-Tier Model

In keeping with the spoken language analogy, this schema is likened to a CVC syllable; static L segments are joined together by “more sonorous” and “visually salient” M segments. Signs are not restricted to a single HANDSHAPE on the HAND CONFIGURATION tier. Simple schemata for two different types of monosyllabic LML signs are shown in Figure 2.2. GOOD consists of a simple path movement, while OLD incorporates a sign-internal HANDSHAPE change.

![GOOD and OLD Diagram](image)

**Figure 2.2:** Structural differences for GOOD and OLD

The figures above represent the most truncated version of the Hand-Tier schema. Technically, the HAND CONFIGURATION tier is broken up into FINGER POSITION, ORIENTATION, and SELECTED FINGERS specifications. The PLACE tier denotes the general PLACE OF ARTICULATION (head, torso, chin, etc.), and the SETTING tier contains two nodes, each linked to one of the L segments. This allows for a more precise rendering of the path movement for each sign, by including both the region of articulation and the hand’s beginning and
endpoints within said region. Figure 2.3 below shows GOOD and OLD in their full Hand-Tier representations:

![Figure 2.3: Full Hand-Tier representations of GOOD and OLD](image)

Note that the FINGER POSITION, ORIENTATION, SELECTED FINGERS, and SETTING nodes are vertically aligned with each L segment, showing the specifications for all tiers at each location in space. The FINGER POSITION tier for OLD has two specifications, [cupped] and [closed], illustrating its sign-internal HANDSHAPE change.

As demonstrated in del Giudice (2007) and Sandler (2011), the Hand-Tier Model excels in its ability to represent the process of compound formation in sign languages. Although compounds are not specifically a focus of this paper, their schematic representations reveal how nodes in the hierarchical structure can spread their features from one constituent sign to another, resulting in a blend of features from two different signs. This idea will become central to my analysis of production phenomena in chapter 6.

In ASL (and sign languages generally), two monosyllabic signs can blend to form a single monosyllabic compound. The formation of the compound FAINT, composed of the constituent signs MIND and DROP, is shown below:

![Fig. 2.4: Compound formation: MIND + DROP → FAINT (truncated structure)](image)
The first sign, MIND, has no internal handshape change. Its second L segment appears as the first L segment in FAINT, but it is linked to the first handshape configuration from DROP. The internal handshape change for DROP is kept intact, with a new starting location. Figure 2.5 below, adapted from Sandler (2011), shows the full-fledged structure of the compound formation:

Figure 2.5: Compound formation MIND + DROP → FAINT (full structure)

The dotted line in the upper image shows the regressive spreading of the hand configuration node in DROP to the second location of MIND (Sandler 2011: 8). The two perpendicular lines in each constituent structure represent segments that are overtaken by the corresponding segment in the other constituent structure, and are thus omitted in the surface representation depicted in the lower image. Del Giudice (2007) provides many more compounds in an appendix, without explicitly diagramming them this way.
To expound on the process of compound formation from a Hand-Tier perspective, I include one more example which has not yet been schematized in the literature. Figure 2.6 shows the truncated Hand-Tier structure for WIFE, which is composed of GIRL and MARRY.

![Figure 2.6: Compound formation GIRL + MARRY → WIFE (truncated structure)](image)

In this case, the compound is formed from two signs with no internal HANDSHAPE change, producing a monosyllabic sign that links the first sign’s HANDSHAPE to its first LOCATION, and the second sign’s HANDSHAPE to its second LOCATION. Here, the HAND CONFIGURATION node from the first sign spreads, with its branching features for internal movement, to the second LOCATION of MARRY. The end result is a sign with an internal HANDSHAPE change:
Though the schema above depicts compound formation fairly well, it also highlights a downfall for which the Hand-Tier Model has been criticized, namely its inability to deal with the movement of the non-dominant hand in two-handed signs (Fenlon et al. 2017: 461). A proper implementation of the non-dominant hand into the model would capture its movement toward the dominant hand, rather than always treating it as a static destination location for the dominant hand.

2.1.2 Prosodic Model

Brentari (1998) introduces a new model that not only rectifies some of the Hand-Tier Model’s structural shortcomings, but also makes a key distinction between INHERENT FEATURES (IF) and PROSODIC FEATURES (PF). INHERENT FEATURES are “properties of signs in the core lexicon that are specified once per lexeme and do not change during the lexeme’s production” (22). These properties include the selected and non-selected fingers of both hands, singularly-specified NMMs, and major body place. PROSODIC FEATURES are the remaining properties of signs that “can change or are realized as dynamic properties of the sign” such as the aperture of the hands, path information, and changes in setting within the major body place. Figure 2.8 below, adapted from Brentari (1998) and Kubuș (2008), shows the binary branching skeletal structure of the Prosodic Model:
The notion of a PROSODIC FEATURE comes from the observation, originally made in Jakobsen et al. (1951), that some features such as [syllabic] and [length] fundamentally differ from other features like [voice] and [nasal] “that can be identified within a single segment by their articulatory or acoustic correlates” (Brentari 1998: 23). PROSODIC FEATURES are a particularly useful concept for sign language analysis because they allow for those properties that change within a single sign to be measured with respect to one another and timed with respect to units larger than the segment, resulting in a more accurate temporal representation.

Syllables are treated differently in the Prosodic Model than in previous models. Instead of separating the syllable into static and non-static components governed by a hand configuration on a higher tier, PM derives the syllable from timing slots – called x-slots – which are generated by the PROSODIC FEATURES. The INHERENT FEATURES are unordered with respect to one another because they are realized at the same time, and spread through an entire prosodic word in core lexemes (Brentari 1998: 184). Therefore, only PROSODIC FEATURES participate in the formation of syllables. The following rule explains the generation of x-slots:

Path features generate two x-slots, and all other prosodic features generate one x-slot. The class node with the highest potential number of x-slots determines the number of x-slots for a particular lexeme.

Brentari (1998: 184)

Path information is the most influential component in the formation of syllables in PM, just as it is in the previously described models, though the timing of the other PROSODIC FEATURES are critical as well. Figures 2.9 and 2.10 show the Prosodic Model representations of the aforementioned monosyllabic signs GOOD and OLD, where each PROSODIC FEATURE is aligned to one of the two x-slot timing units generated by the path movement:
Figure 2.9: Prosodic Model representation of GOOD

Figure 2.10: Prosodic Model representation of OLD
The Prosodic Model provides the most sophisticated depiction of how each parameter of the sign factors into syllable structure. Its main downfall is that, unlike with the Hand-Tier Model, there is no obvious way of dealing with compound formation and feature spreading with the Prosodic Model. For this study, the most important idea offered by the Prosodic Model is that signs consist of features from two categories: those that are unchanging, inherent, and have no timing specifications (IF); and those that can change over the course of the sign’s articulation, and have specific timing relations with all other timed features (PF). Later in this paper, I will offer a hybrid of the Hand-Tier and Prosodic Models that distinguishes between INHERENT and PROSODIC features, while satisfactorily representing phonological processes across multiple signs.

2.2 Gaps in the literature

Brentari’s Prosodic Model and Sandler’s Hand-Tier Model have their strengths, though they also share a mutual shortcoming: facial movements are largely neglected in both. Stokoe (1960) ostensibly set a precedent in ASL phonology that permits an NMM-shaped hole in even the most brilliantly intricate models. The Hand-Tier Model ignores mouth movements altogether, without providing an explanation of how either contrastive INHERENT MOUTH GESTURES or MOUTH MORPHEMES fit into the syllabic architecture. This is curious, given that the model establishes a clear hierarchy of feature classes that could easily include nonmanual components of the signs.

The Prosodic Model is slightly better on this front. Its prototypical binary-branching structure places some NMMs in the leftmost ARTICULATOR node on the INHERENT FEATURES side of the tree, as they can be lexically-specified in some signs just like HANDSHAPE and PLACE. This accounts for those contrastive INHERENT MOUTH GESTURES which do not generate any timing units, are specified only once per lexeme, and do not change over the course of the lexeme’s production. Figures 2.11 shows the PM structure for LATE and NOT-YET, which differ only in the presence of the contrastive TH INHERENT MOUTH GESTURE.
There is also an optional NMM node on the rightmost PROSODIC FEATURES branch, which accounts for the contrastive IMGs that are realized sequentially and thus generate a timing unit. FINALLY and SUCCESS, which differ in the presence of the PAH mouth gesture, are illustrated in Figure 2.12.

Figure 2.11: Prosodic Model representation of LATE [-TH] and NOT-YET [+TH]

Figure 2.12: Prosodic Model representation of SUCCESS [-PAH] and FINALLY [+PAH]
Despite including space for NMMs in its binary-branching structure, the Prosodic Model’s treatment of nonmanual components is lacking and not as robust as it could be. Adjectival and adverbial intensifiers (i.e. MOUTH MORPHEMES) are left out. The ASL phonology literature is practically barren when it comes to tackling the grammatical status of prosodic MOUTH MORPHEMES (and classifiers). Any mention of these components comes in the universal form of “suggestions for further research” (Sandler 1989; Brentari 1998; del Giudice 2007). If we hope to build a comprehensive model of ASL phonology, NMMs will have to shed their status as deserted enigmas and find their rightful place alongside the manual elements of the sign.

In addition to gaps in the ASL linguistics literature, there is also a scarcity of sign language-related research in the realm of COVID-19-specific linguistics literature. Recent studies involving the effects of face masks on speech intelligibility and spoken language communication have largely focused on how different mask materials attenuate specific frequency bands in the acoustic signal (Corey et al. 2020; Magee et al. 2020). While such research is relevant and useful for spoken language, it has no application for sign languages. For languages in the VISUAL SPATIAL modality, mask material and weave types do not change the effect of face masks on intelligibility. Instead, the focus must shift to the overall effect of the presence of a face mask. That said, studies comparing transparent and cloth masks would be useful in future research on sign languages, given that the aforementioned “Deaf masks” allow at least some degree of mouth visibility compared to N95, surgical, and cloth masks.

### 2.3 Constraints

The purpose of this brief subsection is not to prepare the reader for heavily constraint-based analyses in the current study, but rather to give a brief explanation of a constraint that has been previously proposed in the literature. Constraints will be referenced sporadically throughout this paper, and they are important to acknowledge insofar as they provide insight into some of the phonological tendencies of ASL. A substantial portion of the ASL phonology literature makes reference to constraints. In this paper I borrow one particular constraint, MONOSYL, detailed below.

Evidence for the typological uniqueness of sign languages comes from the fact that, “unlike spoken languages, sign languages have a proliferation of monosyllabic, polymorphemic words” (Brentari 2011: 702). Of course, spoken languages can achieve this too (e.g. English cat-s), but this phenomenon is far more common in sign languages and occurs in morphologically complex words such as compounds and directional verbs, as well as classifier constructions. In his analysis of compound formation, del Giudice (2007) captures this tendency towards single-syllable forms with the following markedness constraint:

\[ \text{MONOSYL: Signs must consist of single syllables of the shape LML or L.} \]

The preference of sign languages to minimize syllable count while maximizing morpheme count is well-discussed in the literature. Fenlon et al. (2017) note that 83% of the lexical entries in Stokoe et al. (1965) are “composed of single sequential movements.” This
monosyllabic structure is “retained even when signs are meaningfully modified in a number of ways,” exemplifying “a substantial difference between sign languages and spoken languages” (461). In my analysis of minimal pairs and INHERENT MOUTH GESTURES, I will show how the monosyllable constraint is challenged by ANTI-HOMONOMY, a pragmatic markedness constraint that forces the avoidance of homonymy when the face is obstructed.

2.4 Summary

This chapter highlighted key concepts from existing models of ASL syllable structure that will play an important role in the analysis of my own experimental results. The Hand-Tier Model allows for an accurate representation of parameter-specific feature spreading across signs, while the Prosodic Model distinguishes between singularly-specified INHERENT FEATURES and timing-specified PROSODIC FEATURES. Neither of these models address NONMANUAL MARKERS as thoroughly as they could, but they establish solid groundwork for doing so. In the following sections, I detail my experimental study and results, and provide analyses for the three types of mouth movements in question.
Experimental design and stimuli

I designed a multi-part experiment to test how face masks affect perception and production of the three types of mouth movements. In the broadest sense, the goal of this experiment was to identify what kinds of signals ASL users look for when viewing masked signers, and to determine whether those signals are amplified in masked production. Production tasks were intended to elicit as many mouth movements and classifier handshapes as possible. SPOKEN LANGUAGE MOUTHING tasks were designed to determine to what extent these optional mouth movements aid in perception, and whether hearing status is a factor in the rate of mouthing in production. In the INHERENT MOUTH GESTURE perception portion, accuracy and response times were tested as the face was blurred and masked, to detect default interpretations for IMG-based minimal pairs. Finally, MOUTH MORPHEME perception tasks targeted the interaction between the primary mouth articulation and the secondary eyebrow and body articulations, and their individual roles in conveying intensified meaning.

3.1 Methodology

The experiment was administered remotely due to COVID-19 restrictions, and therefore complied with the Yale IRB social distancing policy for human subject research. All sessions were conducted via the Zoom video conferencing software. Participants opened the experiment on their browser and completed the tasks while sharing their computer screen, as I followed along and ensured that there were no errors or software crashes.

The individual tasks were assembled using the Gorilla.sc experimental protocol, which allows researchers to upload picture or video stimuli, create rich-text activity windows, randomize stimuli, and build spreadsheet-driven experiments that populate response time and accuracy data automatically into an Excel spreadsheet. Once the participant has completed the study, the researcher can download the data from each task and combine the Excel spreadsheets into a comma-separated values (CSV) file, for analysis in data science software such as R (used in this project).

Participants’ anonymity was protected by storing all recorded Zoom meetings on a personal password-protected external hard drive. Each participant was coded in the data spreadsheets with a numerical identity. The Zoom meetings were erased from the external hard drive when this thesis was submitted for initial review.

3.1.1 Session layout

Itineraries for the first and second sessions are provided below.
<table>
<thead>
<tr>
<th>Task</th>
<th>Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Storyboard #1: <em>The Wind and the Sun</em></td>
<td>A picture-by-picture illustrated version of the story <em>The Wind and the Sun</em> is shown with sentences beneath each picture. Participants click through the images while reading the story. Then the story is shown again, without the sentences. They click through the series of illustrations, signing each scene as descriptively as possible. There is an option to view the version with sentences one more time before signing.</td>
</tr>
<tr>
<td>2</td>
<td>Mouthing perception (first half)</td>
<td>A series of 96 video clips are shown (of 192 total for the session), in which a signer produces a single sentence with a target word. This is followed by a question with three response options, and participants choose the best response. Each version of session 1 contains six target words: two core manual signs, two fingerspelled loans, and two lexicalized fingerspelled signs (these are fingerspelled signs which have taken on an additional parameter, such as a path movement or location specification). Throughout the task, each target word appears with various levels of face blurriness, various degrees of redundant mouthing, and across mask conditions. They also occur in both topicalized (sentence-initial) and sentence final position.</td>
</tr>
<tr>
<td>3</td>
<td>Sentence translations #1: Minimal pairs</td>
<td>Participants translate English sentences into ASL. These sentences target INHERENT MOUTH GESTURES.</td>
</tr>
<tr>
<td>4</td>
<td>Picture descriptions #1</td>
<td>A series of six images is shown. Each image stays on the screen for 30 seconds, during which participants describe them with as much detail as possible. A countdown timer appears for the last 10 seconds.</td>
</tr>
<tr>
<td>5</td>
<td>Video descriptions #1</td>
<td>A series of seven video clips is shown, ranging from 3 to 30 seconds. Participants may play the clips as many times as they want, before describing them with as much detail as possible.</td>
</tr>
<tr>
<td>Break</td>
<td>Participants are asked to wear a mask for the remainder of the experiment.</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>Storyboard #2: <em>The Tortoise and the Hare</em></td>
<td>Same as task #1, but with an illustrated version of the story <em>The Tortoise and the Hare</em>.</td>
</tr>
<tr>
<td>7</td>
<td>Sentence translations #2: Mouth morphemes</td>
<td>Participants translate English sentences into ASL. These sentences target adverbial and adjectival MMs.</td>
</tr>
<tr>
<td>8</td>
<td>Picture descriptions #2</td>
<td>Same as task #4, but with a different set of images.</td>
</tr>
<tr>
<td>9</td>
<td>Video descriptions #2</td>
<td>Same as task #5, but with a different set of videos.</td>
</tr>
<tr>
<td>10</td>
<td>Mouthing perception (second half)</td>
<td>The remaining 96 video clips are shown.</td>
</tr>
</tbody>
</table>
### 3.1.2 Participants

There were 16 participants total: eight native Deaf, four Hard-of-hearing, and four Hearing signers. All signers were at native fluency in the language. I gathered interest by posting an ASL-signed outreach video to various forums and social media websites, including Facebook, Twitter, the subreddits r/Deaf and r/ASL, and the ASL at Yale (ASLaY) club. The project gained additional exposure thanks to help from the Bellingham, Washington-based Hearing, Speech & Deaf Center.

Each participant completed two one-hour sessions, spread 7-12 days apart, and were compensated $15 per session. Due to the large amount of perception stimuli, there were three versions of the session: V1, V2, and V3. Each version contained half of the overall SPOKEN LANGUAGE MOUTHING stimuli for the study, and the sentences and target words did not

<table>
<thead>
<tr>
<th></th>
<th>Session 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Storyboard #2: <em>The Tortoise and the Hare</em></td>
</tr>
<tr>
<td>2</td>
<td>Inherent mouth gesture perception</td>
</tr>
<tr>
<td>3</td>
<td>Sentence translations #2: Mouth morphemes</td>
</tr>
<tr>
<td>4</td>
<td>Picture descriptions #2</td>
</tr>
<tr>
<td>5</td>
<td>Video descriptions #2</td>
</tr>
<tr>
<td></td>
<td><strong>Break</strong></td>
</tr>
<tr>
<td>6</td>
<td>Storyboard #1: <em>The Wind and the Sun</em></td>
</tr>
<tr>
<td>7</td>
<td>Sentence translations #1: Minimal pairs</td>
</tr>
<tr>
<td>8</td>
<td>Picture descriptions #1</td>
</tr>
<tr>
<td>9</td>
<td>Video descriptions #1</td>
</tr>
<tr>
<td>10</td>
<td>Mouth morpheme perception</td>
</tr>
</tbody>
</table>
overlap across versions; 576 total stimuli were created for SLMs, and each version had 288 SLM items. For example, there were 18 total SLM target words, and each version contained nine (with the full set of face blurring and mask conditions, as explained in Section 3.3.1. All three versions contained all INHERENT MOUTH GESTURE and MOUTH MORPHEME stimuli. V1 was sent to six participants, and V2 and V3 were each sent to five. All participants received the same production stimuli. The two sessions that each participant attended had similar structures.

3.2 Production tasks

There were four types of production tasks: storyboards, sentence translations, picture descriptions, and video descriptions. Sentence translations are discussed in more detail in chapter 5 on INHERENT MOUTH GESTURES. The full set of production stimulus items is listed in the appendix, but brief explanations of the task structures for storyboards, picture descriptions, and video descriptions are included in the next few subsections.

3.2.1 Storyboard tasks

Two classic tales were used for the storyboard portions: The North Wind and the Sun and The Tortoise and the Hare. The former was selected based on its widespread use in phonetic elicitations (Hiki 2013). These stories were useful in targeting the production of classifiers and intensifying MOUTH MORPHEMES; each tale revolves around two central characters with contrasting personalities and physical characteristics who move around substantially and attempt to win a competition using opposing means. The image sequences for both stories were captured from the animated versions produced by PinkFong. At the beginning of the task, participants clicked through the story image by image, reading each caption one-by-one. Captions were intentionally sparse, and included just enough information to keep participants from misunderstanding the pictures:

![Image of a cartoon scene showing a man walking forward while the wind blows harder and harder. Caption: 'The wind blew harder and harder, but the man kept walking forward...']

4 Used with permission.
The instructions encouraged elaboration and description, rather than direct translation. After clicking through the story, participants were allowed to cycle through the images with captions one more time before beginning the picture-only segment, where they translated the story picture-by-picture.

### 3.2.2 Picture description tasks

Each session had two picture description tasks, with six pictures in each task. Participants had 30 seconds to describe a picture with as much detail as possible before the next one automatically appeared. A mix of people, animals, cartoons, and various objects were used. Content was selected based on the likelihood of provoking classifier and MOUTH MORPHEME use. For example, the image of the dogs below reliably elicited WHOLE ENTITY and DESCRIPTIVE CLASSIFIERS, as well as MOUTH MORPHMES for intensifying size and appearance.

![Image of dogs](image1.png)

**Figure 3.1:** An example item from the picture description task

### 3.2.3 Video description tasks

Sessions also contained two video description tasks, each with seven videos. These short clips played automatically upon loading, and participants were allowed to replay them before signing. Again, the selection of these stimulus items was primarily based on the goal of eliciting classifiers and MMs. Video clips included cartoons, news segments, sports clips, and nature footage. All selected items were freely available for non-commercial use under Creative Commons licensing.

![Screenshot of video clips](image2.png)

**Figure 3.2:** Screenshots from example video stimulus items
3.3 Perception tasks

There were three types of perception tasks, one for each mouth gesture type. Since participants were not required to wear a mask for perception, these tasks were not repeated across sessions. The first session contained the SPOKEN LANGUAGE MOUTTHING tasks, and the second session contained the INHERENT MOUTH GESTURE and MOUTH MORPHEME tasks.

3.3.1 SPOKEN LANGUAGE MOUTHING tasks

There were 18 total target words in this task. Three sets of SLM stimuli were distributed across the first session. Each set contained six target words:

- 2 core manual signs
- 2 lexicalized fingerspelled signs
- 2 fingerspelled loanwords

This distribution of sign types allows for an analysis of the differences in response time when words from the core lexicon and non-native lexicon are mouthed.

It has been established that fingerspelled loanwords are part of the non-native lexicon, though it is unclear how lexicalized fingerspelled signs should be categorized. These signs are obviously derived from fingerspelled loanwords, but they have taken on additional sign parameters, to the extent that their citation forms involve a combination of fingerspelling and either path movements or location specifications. These signs are often abbreviated, so that one or more letters are omitted from the fingerspelling action. For example, BANK is signed by fingerspelling #BNK. The sign begins with a B-HANDSHAPE (HS) on the dominant hand, which then moves downward vertically while transitioning to the N-HS, and then up again while transitioning to the K-HS. This manifests as a path movement that looks like a bouncing motion, while the abbreviated word is spelled out:

![Figure 3.3: Lexicalized fingerspelled sign #BNK bank](image)

The basis for including lexicalized fingerspelled signs in the SLM stimuli set was to determine whether the reaction to mouthing for these signs more closely resembles that of core signs or of fingerspelled loanwords. The tables below show the full set of target words for the SLM stimuli set with the corresponding display questions that were shown to participants after they watched the video clips:
Each target word appeared in two signed sentence structures: one in which the word was topicalized in sentence-initial position, and one in which the word was in sentence-final position and introduced by a QUESTION-ANSWER CLAUSE (QAC). After the video stimulus played, a display question automatically appeared with three response button options. Furthermore, each target word was presented with various degrees of face blurring, and across mask conditions. There were four levels of face blurring: 1 (no blur), 2 (33% blur), 3 (66% blur), and 4 (100% blur). The signer’s face was blurred using Final Cut Pro X with a custom vector blur shape that used the eyes as a tracking point to stay in the correct position. This effect was then batch-applied to all stimuli in incremental steps (blur levels 1-4) and any errors in the coordinates of the blur vector were manually adjusted. Finally, each phrase had either no mouthing, mouthing of the target word only, or mouthing of all words. The mask condition is a subset of the mouthing condition, because the use of a mask entails no mouthing (the mouth is not visible at all). Therefore, I have grouped together “target only” mouthing and “all mouthing” to analyze the overall effect of mouthing the target sign type. We have 32 clips for each target word:

\[(2 \text{ sentence positions}) \times (4 \text{ blur levels}) \times (4 \text{ mouthing conditions}) = 32\]

There are six words per set, for a total of 192 clips per set, and 576 stimuli across the three sets. Figure 3.4 shows examples of various combinations:
3.3.1.1 SPOKEN LANGUAGE MOUTHING hypotheses

Given the supposed status of both SLMs and fingerspelled loanwords as borrowed elements from spoken language, we expect to observe a larger difference in response times for mouthed vs. non-mouthed fingerspelled loanwords. These words from the non-native lexicon are expected to take longer to process than signs from the core lexicon because of their lower frequency.

**SLM H1:** Non-mouthed fingerspelled loanwords will elicit significantly longer response times than mouthed fingerspelled loanwords, overall.

Additionally, non-mouthed lexicalized fingerspelled signs are expected to elicit a significantly longer reaction time than mouthed core manual signs, because I hypothesize that, while these forms are not necessarily elements of the non-native lexicon, and should not be grouped together with fingerspelled loanwords, they lie somewhere between loanwords and core signs. They are obviously derived from English loanwords, but have adopted an additional sign parameter which likely means that they are stored in the mental lexicon as such and are more readily accessible than fingerspelled loans.

**SLM H2:** Non-mouthed lexicalized fingerspelled signs will elicit a significantly longer response time than mouthed core signs overall, though not as long as for fingerspelled loans.

For these same reasons, reaction times for core signs are not expected to differ based on mouthing:

**SLM H3:** Non-mouthed and mouthed core signs will show no significant difference in response times.
Since SPOKEN LANGUAGE MOUTHINGS are said to carry no semantic content and thus do not necessarily co-occur with eyebrow movements (the way MOUTH MORPHEMES do), we do not expect to observe any effect of blurring any part of the face other than the mouth. This will be tested with the set of masked stimuli; progressively blurring masked stimuli is effectively the same as progressively blurring the eyebrows for non-mouthed stimuli, because the presence of a mask entails no visible mouthing.

**SLM H4**  
*Response times will not differ across blur levels for masked stimuli.*

If mouthing is related to word frequency and *core* vs. *non-core* elements, we will expect to see a difference in the rate of mouthing across the three word types. Core manual signs should be mouthed the least, and fingerspelled loanwords should be mouthed the most.

**SLM H5:** *Fingerspelled loanwords will be mouthed at a significantly higher rate than lexicalized fingerspelled signs, which will be mouthed at a significantly higher rate than core manual signs.*

### 3.3.2 INHERENT MOUTH GESTURE tasks

The three sets of minimal pairs/triplets discussed in section 1.6.2.3 were tested. Each set had two or three sentence frames, where both (or all three) of the target words were equally plausible in context. The goal in designing these stimuli was to test the default understanding of signs from a minimal pair when the mouth was blocked, and to observe the effect of face blurring and masks on accurate sign identification.

<table>
<thead>
<tr>
<th>Response options</th>
<th>Mouth gesture tested</th>
<th>Sentence frame</th>
<th>Display question</th>
</tr>
</thead>
<tbody>
<tr>
<td>SUCCESS / FINALLY</td>
<td>PAH / ∅</td>
<td>DRIVING TEST ME PASS. _</td>
<td>What was the final sign?</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Isolated sign</td>
<td>What was the sign?</td>
</tr>
<tr>
<td>LATE / NOT-YET</td>
<td>TH / ∅</td>
<td>MY PLANE DEPART _</td>
<td>What was the final sign?</td>
</tr>
<tr>
<td></td>
<td></td>
<td>STUDENT ARRIVE-AT CLASS _</td>
<td>What was the final sign?</td>
</tr>
<tr>
<td></td>
<td></td>
<td>HOMEWORK ME SUBMIT _</td>
<td>What was the final sign?</td>
</tr>
<tr>
<td>SHOULD / MUST / NEED</td>
<td>SH / MUH / ∅</td>
<td>HOMEWORK YOU _ DO</td>
<td>What was the sentence?</td>
</tr>
<tr>
<td></td>
<td></td>
<td>SAVE MONEY ME _</td>
<td>What was the final sign?</td>
</tr>
</tbody>
</table>

As with the SPOKEN LANGUAGE MOUTHING stimuli, all target signs appeared across the mask condition, and with blur levels of 1-4. Participants could choose either of the two members of
the IMG-based minimal pair as their answer. Both response time and accuracy were automatically recorded by the Gorilla.sc protocol and populated into an Excel spreadsheet for later analysis.

3.3.2.1 INHERENT MOUTH GESTURE hypotheses

Accuracy is expected to decrease for unmasked stimuli as the face is progressively blurred, but should stay constant for masked stimuli. Again, eyebrow movements are assumed not to contribute to INHERENT MOUTH GESTURES, so for masked stimuli, the visibility of the eyebrows should be of no help to participants in correctly identifying members of IMG-based minimal pairs. For unmasked stimuli, progressively blurring the face represents progressive obfuscation of the mouth, so accuracy should decrease as the face is progressively blurred. This hypothesis also applies to response times:

**IMG H1:** Response time and accuracy will decrease with progressive face blurring for unmasked stimuli, but will stay constant for masked stimuli. As the face reaches total blurriness, the odds of choosing either minimal pair sign will approach chance.

As for the default interpretation of the minimal pair (or minimal triplet) signs, sign selection is expected to be random when the mouth is obscured. When a sign parameter is blocked and context is not informative for suggesting one choice over the other, there should be no assumption that the parameter is specified in a particular way or not. If two signs which differ only in HANDSHAPE (e.g. NEPHEW and MALE-COUSIN) were to be distinguished when the hands were blurred in a context that would reasonably allow either word, we would not expect a default interpretation of one sign over the other.

**IMG H2:** For masked stimuli, the odds of participants selecting one minimal pair sign over another will not significantly differ.

Note that this hypothesis is only somewhat well-founded, given that there are virtually no examples of minimal pairs that differ in the presence of a parameter altogether, other than these IMG-based minimal pairs. HANDSHAPE, PALM ORIENTATION, LOCATION, and MOVEMENT are always specified for lexical items, so the only minimal pairs we observe for these parameters are those that differ in parametric specification rather than the actual existence of any parametric specification. This assumed lack of any default interpretation should be reflected in production as well:

**IMG H3:** In production, signers will not make any adjustments while wearing a mask. [+IMG] and [-IMG] signs will be articulated normally, even though signers do not have access to the IMG.
### 3.3.3 MOUTH MORPHEME tasks

These tasks were designed to determine whether the presence of a MOUTH MORPHEME alone is sufficient to indicate intensity in adjectives and adverbs, or whether the corresponding eyebrow and body movements associated with particular MMIs are required for an intensified reading. Six mouth morphemes were tested. This portion of the experiment was entirely visual; no words appeared on participants’ screens, and the response buttons were images. Each set of image response buttons suggests a spectrum of either adjectives or adverbs, where the two images in the center are more neutral and the images on the far left and right are intensified.

There are two potential adjectives or adverbs for each sentence, and thus each screen presents one of two forced decision tasks. It is assumed that, for example, participants will only choose one of the two righthand images for a sentence frame that is intended to suggest carelessness or sloppiness, and that they will not choose either of the lefthand images which suggest carefulness. For most of the screens, there are two distinct possible signs that could be modified, which no proficient user of ASL would mix up.

<table>
<thead>
<tr>
<th>Sentence frame</th>
<th>Mouth morpheme tested</th>
<th>Neutral → intensified</th>
<th>MM intensifier type</th>
</tr>
</thead>
<tbody>
<tr>
<td>MY HOUSE _</td>
<td>OO</td>
<td>small → very small</td>
<td>adjective</td>
</tr>
<tr>
<td></td>
<td>CHA</td>
<td>large → very large</td>
<td></td>
</tr>
<tr>
<td>MY CAR _</td>
<td>OO</td>
<td>dirty → filthy</td>
<td>adjective</td>
</tr>
<tr>
<td></td>
<td>CLENCH</td>
<td>clean → very clean</td>
<td></td>
</tr>
<tr>
<td>MY DOG _</td>
<td>OO</td>
<td>thin/small → very thin/small</td>
<td>adjective</td>
</tr>
<tr>
<td></td>
<td>PUFFED</td>
<td>fat/large → very fat/large</td>
<td></td>
</tr>
<tr>
<td>ME DRIVE _</td>
<td>PRESS</td>
<td>carefully → very carefully</td>
<td>adverb</td>
</tr>
<tr>
<td></td>
<td>TH</td>
<td>carelessly → very carelessly</td>
<td></td>
</tr>
</tbody>
</table>
In some stimuli, the signer used only the mouth component of the tested MOUTH MORPHEME. In others, the signer engaged either the corresponding eyebrow movements, body movements, or both. Each of the two adjectives or adverbs were presented in the following conditions (the driving example above is used to illustrate):

![Images of signers with masks and without, showing different combinations of body and eyebrow movements.](image)

**Figure 3.5:** (a) Mask, body, brows; (b) Mask, brows; (c) Mask, body; (d) No mask, MM, brows, body; (e) No mask, MM, brows; (f) No mask, MM, body; (g) No mask, MM

### 3.3.3.1 MOUTH MORPHEME hypotheses

No significant difference is expected between the rate of intensified readings between masked and unmasked stimuli in which only the mouth component of the MM is used (and not the eyebrows or body). This hypothesis is based on the claim that “MOUTH MORPHEMES involve more than just the mouth,” and require co-occurring body and eyebrow movements in order to modify adjectives and adverbs (Bickford & Fraychineaud 2006). For example, if the signer in the stimuli describes his manner of driving using the mouth component of the TH MOUTH MORPHEME alone, without adjusting his body and eyebrow movements accordingly, the verb will not be understood as intensified (i.e. extremely careless). Adjectival and adverbial MOUTH MORPHEMES are not merely specifications for mouth movements, but rather “packages” of gestures which necessarily include the eyebrows and mouth.

**MM H1:** The interpretation of MMs that only contain their mouth components will be neutral rather than intensified, and there will be no significant difference between the likelihood of intensified interpretations across mask conditions. The more elements (e.g. eyebrow and body movements) that are added, the more likely participants will be to get an intensified reading.

Signers are expected to be conscious of the fact that, while wearing a mask, their mouths are obstructed and thus MOUTH MORPHEMES are impossible to fully articulate. They will make greater use of eyebrow and body movements (the components of the MM that are still available during masked signing) to make up for the unavailability of the mouth.

**MM H2:** While wearing a mask, signers will articulate MOUTH MORPHEMES by using more exaggerated eyebrow and body movements, as a strategy for preserving the evidence of the mouth movement behind the mask.
SPOKEN LANGUAGE MOUTHINGS: Differences in Deaf and non-Deaf behavior

The next three chapters take the reader through the experimental findings for each of the tested mouth gestures: SPOKEN LANGUAGE MOUTHINGS, INHERENT MOUTH GESTURES, AND MOUTH MORPHEMEs. Perception and production results are reported, followed by a linguistic discussion and analysis of the findings. We begin with the perception findings for SPOKEN LANGUAGE MOUTHINGS.

4.1 Perception of SPOKEN LANGUAGE MOUTHINGS

Response times were longer for masked stimuli overall. F-tests revealed a statistically significant difference of variance between the two distributions shown in Figure 4.1 ($p < .05$). Across all word types, the presence of a mask diminished word recognition speed. The following subsections further investigate the degree to which words from different parts of the lexicon were affected by mouthing, and the divergent results based on hearing status.

![Figure 4.1: Response time distribution across mask conditions](image-url)
4.1.1 Response time by word type

It is necessary to break up the stimuli by target word type to evaluate the hypothesis regarding differences in response time effects for core signs, lexicalized fingerspelled signs, and fingerspelled loanwords. Overall (across all mask and mouthing conditions), the RT distributions look similar, though fingerspelled loans have a wider distribution (i.e. higher variability) than core and lexicalized fingerspelled signs. Further separating target word type by mouthing condition, we observe a more salient effect:

![Fig. 4.2: Overall response time distributions by word type](image)

**Figure 4.2:** Overall response time distributions by word type

This figure provides evidence in support of hypotheses SLM H1 and SLM H3 (see p.35); the effect of mouthing on response time was the largest for fingerspelled loanwords, and there was very little effect on core manual signs. SLM H2, however, is refuted here. Lexicalized fingerspelled signs underwent no real effect of mouthing, suggesting that these lexemes should probably categorized as core signs themselves. Of course, the effect of mouthing on response time for a given lexical item is by no means the only relevant dimension for classifying it as a member of one section of the lexicon over the other, but with this data alone it is clear that lexicalized fingerspelled signs are much more similar to core signs than to loanwords.

The lower frequency of *non-native* items may be an explanation for why they are more susceptible to response time effects due to mouthing. Another potential explanation is that, when a signer mouths a fingerspelled word, the watcher is able to focus on the mouth to identify the word, rather than having to process the manual spelling, which takes longer to comprehend.
4.1.2 Face blurring effects

Across all conditions, progressive face blurring had a weak effect on response time ($r = 0.143$). When we separate the masked and unmasked stimuli, however, we find a clear difference in effect across the mask condition (Figure 4.4). Response times increased for unmasked stimuli as the face became blurrier, but there was no change for unmasked stimuli. This result suggests that non-mouth cues have no effect on the perception of SLMs. For masked stimuli, the eyes and eyebrows are the only visible part of the face, so we can take the slope of the red line to represent the effect of blurring just the eyes and eyebrows (while keeping mouthing stable at zero).

Having established that obfuscation of the eyes and eyebrows have no effect on the perception of SLMs, we can take the blue line to represent the effect of progressively blurring the mouth alone. SLMs provide no lexical contrast or additional semantic meaning, so they are completely separable from all additional cues; any effect of face obfuscation on response time for SLMs is due to the mouth alone. Hypothesis SLM H4 (see p. 36) is supported; masked stimuli did not exhibit any change in response time as the face was progressively blurred.

4.1.3 Hearing status as a factor

Participants’ hearing status proved to play a role in the response time reactions to the presence or absence of SLMs. While there was considerable variation in the reaction to mouthed vs. unmouthed words, the presence of mouthing had a noticeably higher effect on response times for Hearing and Hard-of-hearing participants than for Deaf participants.
In Figure 4.5 above, the distribution of response times for each participant is represented by a pair of box plots, side-by-side. The darker-colored box of a given pair is the distribution for mouthed words, and the lighter-colored is the distribution of non-mouthed words. For example, participant p101’s distributions are shown on the far left of the figure; their response times (dark salmon color) were shorter overall for mouthed words than for non-mouthed words (light salmon color). Distributions for Deaf participants are much closer together than for Hearing and Hard-of-hearing participants. In some cases (p107 and p108), Deaf participants actually responded faster to mouthed words. The blue and green sections of the graph indicate a much larger effect of SLMs on response times for Hearing and Hard-of-hearing participants (p109–p116). Figure 4.6 below groups participants together by hearing status:

Figure 4.6: Differences in response time across mouthing conditions, by hearing status

Given the similar effect of SLMs on Hearing and Hard-of-hearing participants, we categorize them together as a “non-Deaf” group, as shown in Figure 4.7:

Figure 4.7: Hearing and Hard-of-hearing participants categorized as “non-Deaf”

SPOKEN LANGUAGE MOUTHINGS had a statistically significant decreasing effect on response time for the non-Deaf group, while the Deaf group was not significantly affected:

43
4.1.4 Mixed effects model for response time

A mixed effects model was used to determine the significance of the effect of each tested predictor on response time. ANOVA model comparison verified that the best model was the one that included trial number, the mouthing condition, and target word type as fixed effects. “Target word” was included as a random effect to capture the idiosyncratic variability of the specific words used in the task. Additionally, a random effect was added for “Participant” with a random slope for mouthing condition by participant.

\[
\text{lm}er(\text{logRT} \sim \text{Trial.Number} + \text{Mouthing\_Grouped} + \text{TargetWordType} + (1|\text{TargetWord}) + (1+\text{Mouthing\_Grouped}|\text{ParticipantID}), \text{data}=\text{md\_excluded}, \text{REML}=\text{FALSE})
\]

<table>
<thead>
<tr>
<th></th>
<th>Mean log RT</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mouthing</td>
<td>No mouthing</td>
<td></td>
</tr>
<tr>
<td>Deaf</td>
<td>6.91</td>
<td>6.90</td>
<td>-0.17</td>
</tr>
<tr>
<td>non-Deaf</td>
<td>6.77</td>
<td>7.11</td>
<td>-11.01</td>
</tr>
</tbody>
</table>

Table 4.1: Fixed effects for SLM model. Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’

Trial number, mouthing condition, and target word type were statistically significant predictors of response time. The intercept in the model above is the estimate log response time when the reference levels are met (i.e. when trial number is 0, for non-mouthed core signs). Adding blurriness as a fixed effect significantly weakened the model.

4.2 Production of SPOKEN LANGUAGE MOUTHINGS

There were no discernible alternative communication strategies for masked signers across the hearing status condition with regard to SLMs. Generally, if an unmasked signer mouthed an English word or syllable while articulating a manual sign, there was no adjustment to the articulation of the same sign when the signer wore a mask. Considering their inconsequential status in ASL grammar, it is no surprise that SLMs can be omitted or blocked without causing any repercussions for the manual components of the sign. The primary findings for SLM perception parallel those illustrated in the previous sections on SLM perception. In particular, word type and hearing status were the two factors responsible for differences in mouthing rate and the complexity of mouthed segments.
4.2.1 Mouthing rate across word types

In the previous section on SLM perception, I showed that the presence of mouthing had the most drastic effect on the response time of fingerspelled loanwords, compared to core manual signs and lexicalized fingerspelled signs. A complementary pattern emerged in production tasks. Deaf and non-Deaf participants showed a much higher rate of mouthing for fingerspelled loanwords (non-core items) than for core items. To manually mark every sign from each one-hour session as “mouthed” or “unmouthed” would be virtually impossible without the aid of a highly intelligent automated program, since the average signer can easily produce around 150 discrete signs per minute (Bellugi & Fischer 1972; Grosjean 1977). Instead, for each participant’s unmasked production session, I counted the number of total fingerspelled forms to calculate the average rate of fingerspelling per minute. Additionally, I noted the word type for each overtly mouthed form to determine the breakdown of mouthing rate across word types.

All participants averaged between 0.8 and 1.2 fingerspelled forms per minute. If we conservatively estimate the overall signing rate across participants to be 120 discrete signs per minute, fingerspelled forms account for 1% or less of all signs. Fingerspelled forms made up 30-40% of all mouthed signs for each participant. Non-native fingerspelled loanwords – the least common word type by far – are responsible for a hugely disproportionate amount of overall mouthing.

Hypothesis SLM H5 (see p. 36) is only partially supported; loanwords were mouthed at a significantly higher rate than lexicalized fingerspelled signs, but lexicalized fingerspelled signs and core manual signs were mouthed at a roughly equal rate. This provides further motivation for categorizing the latter two word types as part of the same core group in the lexicon.

4.2.2 Deaf vs. non-Deaf mouthing

There was no significant difference in the rate of mouthing during production tasks between Deaf and non-Deaf signers, and all participants showed the same basic pattern of increased mouthing for fingerspelled loanwords. However, the general structure of the silent articulations for mouthed English words was noticeably different depending on hearing status. While non-Deaf participants tended to mouth entire words, Deaf participants almost universally mouthed the stress-bearing syllable(s) alone. This pattern held for all word types. Figures 4.8 (a) - (c) below show the different mouthing tendencies between Deaf and non-Deaf signers for core manual signs (a), lexicalized fingerspelled signs (b), and fingerspelled loanwords (c):
Many of the stress-bearing syllables selected for mouthing by Deaf participants were only partially mouthed, like those in (a) and (b) above. Syllable nuclei were consistently reflected in Deaf mouthing, as were the majority of onsets regardless of place of articulation. Closed syllables were particularly susceptible to reduction, with CVC structures routinely surfacing as CV_. The only exception to this rule was observed in syllables with [+labial] codas:
Figure 4.9: Deaf SLM articulations of labial codas

4.3 Discussion

4.3.1 Differences based on hearing status

The fact that Deaf and non-Deaf participants perceived and produced SLMs differently suggests a contrast in how these two groups conceptualize the mouthing action itself. The immediate temptation may be to attribute any observed discrepancies in SLM perception and production between Deaf and non-Deaf signers to the difference in linguistic input for the two groups. One could reasonably speculate that non-Deaf signers are able to leverage their auditory processing ability when viewing silent speech articulations, in tandem with the visuospatial processing required to understand the manual elements of signs. If this were the case, then Deaf signers would conversely be limited to visuospatial processing and unable to make use of silent speech articulations for perception, leading to our observed results that show a negligible effect of SLMs on reaction times for Deaf signers, and a significant effect for non-Deaf signers.

However, it is actually not the case that brain activation differs across language modalities; there is no separate visuospatial area of the brain reserved for sign processing. Neuroimaging studies on both spoken and signed language users have shown similar localization patterns. In Hearing individuals, the left hemisphere is “generally considered dominant for language processing, while the right hemisphere is specialized for visuospatial
functions” (MacSweeney et al. 2002: 1584). Hearing patients with brain lesions in the inferior prefrontal or superior temporal regions of the left hemisphere have exhibited Broca’s aphasia or Wernicke’s aphasia, respectively. Damage to Broca’s area tends to cause agrammatical and incomplete speech, while damage to Wernicke’s area engenders a fluent aphasiac condition where speakers produce phrases with typical speech rate and logical syntax, but meaningless words (DeWitt & Rauschecker 2013: 184).

Sign language users with damage to Broca’s or Wernicke’s area suffer the same aphasia patterns resulting in agrammatical signing or fluent sign aphasia (Capek et al. 2008; MacSweeney et al. 2002). It is safe to say, then, that signs are processed linguistically first and foremost despite their visual nature; signed and spoken languages are not stored and accessed as fully distinct cognitive systems, but instead model strikingly similar patterns of lateralization (Morford et al. 2019: 1-2).

The observed difference in the effect size of SLMs on response time across the hearing condition may be attributed to a mixture of bilingual activation and multisensory integration, two phenomena that are presumably available only to non-Deaf participants. Eye-tracking studies of cognate processing in spoken language bilinguals have shown that, when presented with a set of words from the nontarget language that vary in phonological similarity with their translations in the target language, participants tend to fixate faster on the most phonologically-similar forms. Bilingual activation occurs for words that have significant phonological overlap across the two languages; activation of a word in one language supports processing in the other (Marian & Spivey 2003; Blumenfeld & Marian 2005; Thierry & Wu 2007; Martínez-García 2019).

Of course, the notion of “phonological similarity” does not naturally map onto the polymodal situation presented in this experiment. Rather than reading or hearing words from the nontarget language (English) in isolation, in this case bilingual non-Deaf signers viewed SLMs and manual signs simultaneously. Auditory and visual information have been shown to integrate for hearing individuals in speech perception (McGurk & MacDonald 1976; Macaluso et al. 2004; Tsilionis & Vatakis 2014). It is difficult to say for sure whether this sort of multisensory integration is at play here, but it may be the case that the presence of SLMs trigger bilingual activation in non-Deaf signers when the visual signal from the silent speech articulation is linked symbolically to the auditory “signal” that the SLM represents. Regardless, the disparate effect of SLMs on reaction time across the Deafness condition is likely due to the enhanced lexical activation that comes with bilingualism, and not to any fundamental differences in the linguistic processing mechanisms for Deaf vs. non-Deaf signers.

4.3.2 Effects of lexical frequency

It is not entirely clear why items from the non-native lexicon were highly affected by English mouthing in perception and production tasks. It may be the case that English mouthing is a phonetic enhancement operation which applies most readily to low-frequency items. In spoken language, phonetic enhancement can appear in the form of hyperarticulatory actions like increased voice onset time (VOT) for consonants, expansion of the vowel space, increased vowel length, and widened pitch range (Goldrick et al. 2011; Wedel et al. 2018; Zellou & Scarborough 2019; Bell et al. 2009). It has been shown, for example, that for homophonous
pairs, the lower-frequency, less predictable item (e.g. *thyme*) tends to be longer than its higher-frequency counterpart (e.g. *time*) (Gahl 2008). Low-frequency items may be associated with narrower ranges of phonetic variation than high-frequency items. As a result, low-frequency words “indicate that a specific set of acoustic or articulatory properties should be present phonetically” (Goldrick et al. 2011: 62).

Words from the non-native lexicon are of course less frequent in ASL discourse. English mouthing, which is neither obligatory nor contrastive in the language, may be one of these articulatory properties that is more likely to co-occur with low-frequency non-native fingerspelled forms than with high-frequency signs from the native lexicon. This analysis assumes that mouthing is a form of phonetic enhancement that aids in perception. It is also possible that fingerspelling itself is a form of phonetic enhancement used for low-frequency words, and that concomitant English mouthing is an extension of the enhancing property; if an item is rare enough to require fingerspelling, then it will also require mouthing.

4.4 Summary

In this chapter, SPOKEN LANGUAGE MOUTHINGS were shown to aid in non-Deaf sign perception more than in Deaf sign perception. In light of the fact that Hearing and Hard-of-Hearing participants patterned similarly in their perception of SLMs, there may be a significant effect of bilingualism on how heavily a given signer relies on English mouthings for sign identification. The structure of SLMs in sign production was furthermore shown to differ based on hearing status. Of the three mouth movement types under consideration in this project, SPOKEN LANGUAGE MOUTHINGS are the least contrastive in the language, and thus the least consequential in ASL grammar. It is not surprising, then, that obstructing the face did not elicit any real alternative communicative strategies in production, and that only response times in perception suffered as a result of the presence of a face mask. In the next chapter, I focus on the lexically-contrastive INHERENT MOUTH GESTURES, for which face obstruction catalyzes more severe adjustments in sign production.
INHERENT MOUTH GESTURES:
Default interpretations and homonymy avoidance

Now we turn to the experimental findings and resulting discussion for INHERENT MOUTH GESTURES, the lexically-encoded mouth movements that generate minimal pairs. When a mask is present, the default interpretation is shown to be biased toward the members of IMG-based minimal pairs without an IMG specification (i.e. [–IMG] signs). This phenomenon is apparent in both perception and production. An ANTI-HOMONYMY constraint is proposed as the source of these observations, and pragmatic literature on cooperative discourse is discussed.

5.1 Perception of INHERENT MOUTH GESTURES

The perception section of the previous chapter was specifically concerned with response time as a responding variable. Since our primary focus for IMGs is the default interpretation of signs, most of the analysis in this section will relate to accuracy rather than response time. Nevertheless, some response time data is presented here to begin with.

5.1.1 Response time effects

In contrast to what we observed for SPOKEN LANGUAGE MOUTHINGS, the response time distributions across mask conditions are basically the same for INHERENT MOUTH GESTURES.

Figure 5.1: Response time distribution across mask conditions
Furthermore, blurriness level had no significant effect on response time across mask conditions (Figure 5.2). It is clear that response time for INHERENT MOUTH GESTURES is essentially unaffected by changes in face obfuscation, in contrast to SPOKEN LANGUAGE MOUTHINGS. The first part of IMG H1 is refuted, because response time did not decrease with progressive face blurring for unmasked stimuli.

We can take this to mean that, since IMGs are encoded into the phonology of these lexical items just like other parameters of the sign, differentiating between two signs in an IMG-based minimal pair does not take any extra processing time.

5.1.2 Accuracy effects

Face blurring had a strong effect on the proportion of accurate responses for unmasked stimuli, while there was no correlation between blur level and accuracy for masked stimuli (Figure 5.3). For unmasked stimuli, as the level of blurriness changes from clear to very blurry, the proportion of accurate responses approaches chance. The second part of hypothesis IMG H1 is confirmed. This result suggests that visibility of the mouth is essential for identifying the correct member of an IMG-based minimal pair, and that non-mouth facial cues (e.g. eyebrow movements) are not essential for identifying IMGs.

We can take the red “Mask” line in Figure 5.3 to represent the effect of obscuring parts of the face other than the mouth, since masked stimuli have zero mouth visibility by default. Thus, the manipulated variable for progressively-blurred masked stimuli is the visibility of non-mouth facial movements. If the non-mouth facial movements played a role in minimal pair sign identification, we would expect to see a decrease in accurate responses for masked stimuli as blurriness increases.

5.1.2.1 Hearing status and mouth gestures as (non-) factors

The aforementioned effect of blurriness on accuracy across mask conditions held for non-Deaf and Deaf participants; both groups were less and less accurate as the face became blurrier in unmasked stimuli.
In the perception results for SPOKEN LANGUAGE MOUTHINGS, we saw that response times differed across mouthing conditions based on hearing status. In the case of INHERENT MOUTH GESTURES, hearing status does not appear to play a role in correct sign identification for IMG-based minimal pairs. This provides further evidence in support of the notion that signs with an inherent, lexically-encoded mouth gesture are learned as a bundle of specified features, and thus all signers (regardless of their hearing status or language background) store these signs in the mental lexicon with the IMGs attached to the rest of the specified features. IMGs have no relationship to spoken language whatsoever, so it is not surprising to see that Deaf and non-Deaf individuals behaved similarly in this portion of the study. The effect of blurriness on accuracy was also similar for all three IMGs that were tested:

Figure 5.5: Effect of blurriness on accuracy across mask condition, for different IMGs
5.1.3 Testing default IMG interpretations

Face masks had an effect on the log likelihood that participants would interpret members of IMG-based minimal pairs as having an IMG specification. In Figure 5.6, “Proportion of IMG sign selection” represents, for example, the ratio of FINALLY [+IMG] and SUCCESS [–IMG] selections across mask conditions. Masks greatly reduced the likelihood that participants would select the sign with a lexically-encoded NMM. There is no unanimous consensus on a default interpretation, but the substantial difference in sign selection across mask conditions shows that if a signer’s mouth is obstructed, the watcher tends to assume the absence of mouth movement altogether. This effect of masks on IMG sign interpretation was statistically significant:

<table>
<thead>
<tr>
<th>Mask</th>
<th>Proportion of [+IMG] selection</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mask</td>
<td>34.6%</td>
<td>-7.79</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>No mask</td>
<td>61.8%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Face blurring also affected IMG sign interpretation. As the face became blurrier and nonmanual information was progressively lost, participants were less and less likely to interpret signs as having an IMG specification.

For all three IMGs (PAH, TH, and SH/MUH) progressive face blurring reduced the likelihood of [+IMG] selection in unmasked stimuli. The figures for TH and SH/MUH look quite similar, though PAH shows a decrease in [+IMG] selection not only for unmasked stimuli, but for masked stimuli as well. This is likely due to the fact that the articulation of PAH requires an
exaggeratedly low jaw position. The PAH gesture may be interpretable even if a signer is masked, because the movement of the mask downward suggests jaw movement. As the face became blurrier, that jaw movement was more and more obscured, and participants no longer picked up on any visual cue for PAH.

5.1.4 Mixed effects model for accuracy

A mixed effects model was used to determine the significance of each tested predictor on the likelihood of a correct response. The strongest model included blurriness, mask condition, and an interaction between them as fixed effects. “Sentence” was included as a random effect to account for any variability due to the sentences selected for the task.

\[
\text{glmer}(\text{Correct} \sim \text{Blurriness} \times \text{Mask\_Condition} + (1|\text{Sentence}) , \text{data}=\text{asdf, family=binomial})
\]

| Estimate | Std. Error | z-value | Pr(>|z|) |
|----------|------------|---------|----------|
| (Intercept) | 4.172 | 0.468 | 8.91 | *** |
| Blurriness | -1.139 | 0.136 | -8.39 | *** |
| MaskCondition:Mask | -4.891 | 0.506 | -9.67 | *** |
| Blurriness*MaskCondition:Mask | 0.009 | 0.161 | 7.58 | *** |

Table 5.1: Fixed effects for IMG accuracy model. Signif. codes: 0 :***: 0.001 :**: 0.01 :* : 0.1

All fixed effects are statistically significant predictors of accuracy. The reference levels of this model are met when blur level is 0, and the stimuli is unmasked. The intercept estimate in this model describes the log odds of a correct response over an incorrect response when these reference levels are met.

Blurriness is a continuous factor, so the coefficient here is a slope. This is a glmer model, so the coefficient represents a slope that indicates the change in odds of a correct response over an incorrect response with each increase of 1 in this factor, specifically for unmasked stimuli. In unmasked stimuli, for each increase of 1 unit of Blurriness, the odds of a correct response is reduced by about 70%. Therefore, the odds of a correct response greatly decrease as the face is progressively blurred, for unmasked stimuli.

The Blurriness*MaskCondition:Mask coefficient represents a slope that indicates the change in odds of a correct response with each increase of 1 in Blurriness, for masked stimuli. Thus, in masked stimuli, for each increase of 1 in Blurriness, the odds of a correct response are multiplied by 1.01 (practically no change). The likelihood of a correct response actually increased slightly as the face was blurred for masked stimuli. However, given the design of the experiment, it is likely that this increase in odds is due to chance, as we see that the overall proportion of correct responses for masked stimuli hovers around chance.

Finally, the MaskCondition:Mask coefficient represents the overall change in log odds of a correct response with respect to the reference level condition odds, when the mask
condition is changed from “No mask” to “Mask.” Overall, participants were far less likely to respond correctly to masked stimuli than to unmasked stimuli.

### 5.1.5 Mixed effects model for IMG sign selection

Another mixed effects model was used to determine the significance of predictors on the likelihood that participants would interpret a given sign as having an IMG specification. The best model in this case included blurriness, mask condition, and an interaction between them as fixed effects. “Sentence” and “Participant” were included as random effects.

\[
\textnormal{glmer(MMSelected} \sim \textnormal{Blurriness*Mask\_Condition + (1|ParticipantID) + (1|Sentence)},
\]
\[
\textnormal{data=asdf, family=binomial)}
\]

All fixed effects were statistically significant predictors of IMG sign selection. The reference levels for this model are met when Blurriness level is 0 and the stimuli is unmasked. The intercept estimate describes the log odds of a [+IMG] interpretation over a [-IMG] interpretation when these reference levels are met.

Again, in this model, the Blurriness coefficient is a slope indicating the change in odds of a [+IMG] interpretation with each increase of 1 in this factor, for unmasked stimuli. In unmasked stimuli, for each increase of 1 unit of Blurriness, the odds of a [+IMG] interpretation were reduced by about 42%, meaning that the likelihood that a participant interpreted a sign as having an IMG specification decreased as the face became blurrier.

The Blurriness*MaskCondition:Mask coefficient represents the slope indicating the change in odds of a [+IMG] interpretation with each increase of 1 unit of Blurriness, for masked stimuli. In masked stimuli, for each increase of 1 unit of Blurriness, the odds of a [+IMG] interpretation are multiplied by about 1.13 (very little change); again, this result is likely due to chance.

The MaskCondition:Mask coefficient represents the overall change in the odds of a [+IMG] interpretation with respect to the reference level condition odds, when the mask condition is changed from “No mask” to “Mask.” Participants were far less likely to interpret a sign as [+IMG] for masked stimuli than for unmasked stimuli.

|                     | Estimate | Std. Error | z-value | Pr(>|z|) |
|---------------------|----------|------------|---------|----------|
| (Intercept)         | 1.849    | 0.409      | 4.52    | ***      |
| Blurriness          | -0.548   | 0.102      | -5.39   | ***      |
| MaskCondition:Mask  | -2.356   | 0.394      | -5.98   | ***      |
| Blurriness*MaskCondition:Mask | 0.418 | 0.136 | 3.06 | ***     |

Table 5.2: Fixed effects for IMG accuracy model. Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
5.2 Production of INHERENT MOUTH GESTURES

In the perception portion of the IMG experiment, participants tended to interpret members of an IMG-based minimal pair as the sign without a specified IMG if the signer in the video stimuli was masked. This suggests that when the mouth is blocked, the default understanding is that there is no mouth gesture occurring behind the mask. This tendency was reflected in the production portion of the IMG experiment as well.

In their first sessions, participants were asked to translate sentences that contained one of the two (or three) members of the IMG-based minimal pairs/triplets. Some of the translations occurred at the beginning of the session, before participants were instructed to wear their masks, and some occurred at the end. The sentential frames were designed such that either of the two (or three) members of the IMG-based minimal pairs would be equally sensible in context. Example sentences for each of the three IMG-based minimal pairs are shown below, with the permutations that were presented for each possible word. The set of sentences that targeted PAH and TH also contained a form that forced participants to use both members of the respective minimal pairs/triplets in the same sentence:

(18) Sentence frame: The girl bought a lottery ticket every day. Today, she ____.

- PAH: ... Today, she was successful.
+ PAH: ... Today, she finally won.
+ PAH, −PAH: ... Today, she [finally] [successful].

(19) Sentence frame: The student is ____.

- TH: The student is late to class.
+ TH: The student is not in class yet.
+ TH, −TH: The student [hasn’t done his work yet], and he’s [late] to class.

(20) Sentence frame: I ____ study because I have a test tomorrow.

SH: I should study because I have a test tomorrow.
MUIH: I must study because I have a test tomorrow.
∅: I need to study because I have a test tomorrow.

In the second session, participants translated the same set of sentences again, but this time the mask condition was reversed; all sentences that they had translated while masked in the first session appeared in the unmasked part of the second session, and vice versa. This ensured that every sentence was translated once while masked, and once while unmasked, for both (or all three) members of the IMG-based minimal pair/triplet.

While unmasked, participants largely used IMGs as expected in their translations; members of minimal pairs were mostly articulated in their citation form, regardless of their
IMG specification. Masked signing prompted a major shift in consistency of lexical selection and sign articulation, and brought about a variety of alternative communicative strategies. The signs without an IMG specification were used as normal, but the IMG-specified signs were generally absent when participants were wearing a mask. Participants used synonyms, fingerspelling, and other forms of circumlocution in lieu of FINALLY, NOT-YET, SHOULD, and MUST. No predictable strategy or substitution emerged, other than a general avoidance of IMG-specified signs.

Take the example sentence *The student is not in class yet*, from (19) above, which tests the use of TIl in the IMG-specified sign NOT-YET for masked and unmasked signing conditions. The results for three different participants (p103 – Deaf; p107 – Hearing; p114 – Hard-of-hearing), reported below, encapsulates the consistency in unmasked signing and the variation in masked signing.

<table>
<thead>
<tr>
<th></th>
<th>No mask</th>
<th>Mask</th>
<th>IMG preserved</th>
</tr>
</thead>
<tbody>
<tr>
<td>p103</td>
<td>TIl</td>
<td>TIl, hs</td>
<td></td>
</tr>
<tr>
<td></td>
<td>STUDENT ARRIVE CLASS NOT-YET</td>
<td>STUDENT-IX:RIGHT for-CLASS</td>
<td></td>
</tr>
<tr>
<td></td>
<td>student arrive-at class not-yet</td>
<td>student tardy for-class</td>
<td></td>
</tr>
<tr>
<td></td>
<td>‘The student hasn’t arrived to class yet.’</td>
<td>‘The student is tardy for class.’</td>
<td>IMG → fingerspelling</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>p107</th>
<th>TIl</th>
<th>TIl, hs</th>
<th>IMG preserved</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>STUDENT-IX:RIGHT CLASS NOT-YET arrive not-yet-NEG</td>
<td>STUDENT-IX:RIGHT for-CLASS</td>
<td></td>
</tr>
<tr>
<td></td>
<td>student-3SG class not-yet arrive not-yet-NEG</td>
<td>student-3SG tardy for-class</td>
<td></td>
</tr>
<tr>
<td></td>
<td>‘The student hasn’t arrived to class yet.’</td>
<td>‘The student is tardy for class.’</td>
<td>IMG → fingerspelling</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>p114</th>
<th>TIl</th>
<th>TIl, hs</th>
<th>IMG preserved</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>STUDENT ARRIVE CLASS NOT-YET</td>
<td>STUDENT ARRIVE NOT-YET arrive not-yet-NEG</td>
<td></td>
</tr>
<tr>
<td></td>
<td>student arrive-at class not-yet</td>
<td>student tardy for-class</td>
<td></td>
</tr>
<tr>
<td></td>
<td>‘The student hasn’t arrived to class yet.’</td>
<td>‘The student has not entered the class, but maybe they will soon.’</td>
<td>IMG → circumlocution</td>
</tr>
</tbody>
</table>

It is clear, based on the data above, that participants were conscious of the fact that their mouths were blocked during masked signing, and adjusted their phrasing appropriately for IMG-specified signs. Had there been no default interpretation of IMG-based minimal pairs, we would not expect to see any alternative communicative strategies during masked signing; IMG-specified signs would have been articulated normally despite the obfuscation of the mouth.
5.3 Discussion

The symmetry of perception and production results for IMGs suggests that signers consciously reflect their own default interpretation of minimal pairs during production. In short: in perception, if you cannot see your interlocutor’s mouth, you assume their mouth isn’t moving:

Likewise, in production, if your interlocutor cannot see your mouth, you assume that they assume your mouth isn’t moving, and you adjust your production appropriately to express the correct meaning:

Likewise, in production, if your interlocutor cannot see your mouth, you assume that they assume your mouth isn’t moving, and you adjust your production appropriately to express the correct meaning:
The best explanation for this behavior is more pragmatic than phonological. The Cooperative Principle, introduced in Grice (1975), spells out a pragmatic rule to which speakers and listeners adhere as a means of achieving the most effective communication, and to be mutually understood:

“Make your contribution such as is required, at the stage at which it occurs, by the accepted purpose or direction of the talk exchange in which you are engaged.”

(Grice 1975: 45)

This principle is further divided into four maxims and submaxims of conversation:

1. **Maxim of QUANTITY:** Be informative, but do not be more informative than is required.
2. **Maxim of QUALITY:** Do not say what you believe to be false, and do not say that for which you lack evidence.
3. **Maxim of RELATION:** Be relevant.
4. **Maxim of MANNER:** Be perspicuous. Avoid obscurity, avoid ambiguity, be brief, and be orderly.

(Xiaoqin 2017: 163)

QUANTITY and MANNER are the relevant maxims here. Listeners and speakers (or, in this case, watchers and signers) are expected to be as informative as possible, and as perspicuous as possible. Horn (1984; 1989) compresses Grice’s maxims down into two complementary principles:

Q-PRINCIPLE: Make your contribution sufficient (“Say as much as you can”).

R-PRINCIPLE: Make your contribution necessary (“Say no more than you must”).

In sign language discourse, the signer is expected to make their contribution sufficient for the perceived informative needs of the watcher; discourse participants “look out for one another.” Horn (1984) describes the R-PRINCIPLE as “speaker-oriented,” and thus responsible for various crosslinguistic properties that benefit the speaker (13). For example, synonymy in the lexicon is burdensome for the speaker insofar as intended meaning is easier to precisely express when only one form is available. Avoidance of synonymy is considered “a reflex of the R-PRINCIPLE” that occurs when one form grows a new meaning (Horn 2006: 24). The “hearer-oriented” Q-PRINCIPLE is the R-PRINCIPLE’s mirror image; it is responsible for language changes that benefit the hearer. Homonymy, which is costly for interpretation, is avoided through the growth of a new form for a particular meaning.

The avoidance of homonymy is more restricted than the avoidance of synonymy, because homonymy rarely causes communicative issues in the discourse. Growth of a new
form for a particular meaning is only expected to take place in cases where two words “are alike in sound, when they are common in use in the same social and intellectual circles, [and] when they perform the same syntactical functions in the language, within the same sphere of ideas” (Williams 1944: 5).

ASL certainly allows homonymy; BROWN/BEER and GOOD/THANK-YOU are examples of word pairs that have the exact same parametric specifications. No clarity issues arise for pairs like these, since their distribution in ASL discourse is mutually exclusive. Masks seem to force the growth of a new form in the restricted case of IMG-based minimal pairs, specifically because the members of these pairs are so closely related and can reasonably be substituted for one another.

Masks hinder effective, efficient discourse. Signers and watchers alike have no trouble avoiding obscurity when using and understanding IMG-specified signs, as long as neither are wearing a mask. When masks are introduced, it is no longer sufficient to articulate IMG-specified signs using their manual components alone. Information is lost, and obscurity is increased. There is thus a trade-off between efficiency and clarity. In order to maintain a sufficient level of clarity, signers are forced to be less brief in one way or another. Some signers look for synonyms, while others fingerspell or employ other methods of circumlocution to express their intended meaning.

The observed perception and production behavior for IMGs only bears on ASL phonology in relation to the MONOSYL constraint, argued by myself and others to be a central characteristic property of the language (Sandler 1999, del Giudice 2007; Celli 2020). There seems to be a tendency for ASL to maximize information while minimizing syllable count by any means necessary. The widespread distribution of NMMs in the language is a testament to this tendency toward polymorphemic, monosyllabic prosodic words. However, when the Q-PRINCIPLE is threatened by mask-induced homonymy, brevity and monosyllabicity is sacrificed in service of maintaining clarity. We might then assign a pragmatic ANTI-HOMONYMY constraint which ranks above the MONOSYL constraint. Put briefly, pragmatic clarity outranks phonological economy. From the signer’s perspective, it is more important to be understood than to be maximally brief. Likewise, from the watcher’s perspective, an unambiguous message is preferable to an opaque one, even at the expense of concision.

We are left with one lingering question regarding IMGs: why were the non-IMG-specified signs chosen as the default interpretation over their IMG-specified counterparts? The answer is unclear, especially given that there are no similar examples in spoken language of word pairs that differ in the presence of some feature that is susceptible to removal rather than change in specification. Voicing specification, for example, can distinguish between two phonemes in speech, but there is no way to block voicing as a feature altogether; every segment is either [+voice] or [–voice]. In the case of IMG-based minimal pairs, words differ in the presence or absence of an IMG specification altogether, and masked signing makes it impossible to perceive whether a word is IMG-specified.

One area for future research that may provide insight into this phenomenon is in speech perception among hearing-impaired individuals. Speech recognition studies performed on adults with significant hearing loss above midrange frequencies (>4 kHz) have tested the effects of high-frequency amplification on perceptual accuracy (Ching et al. 1998; Hogan &
Turner 1998; Turner & Cummings 1999). However, these studies have stopped short of proposing default interpretations of natural classes (like voiceless fricatives) that are most heavily affected by high-frequency dampening.

5.4 Summary

The data presented in this chapter shows a default interpretation pattern for INHERENT MOUTH GESTURES. Participants tended to perceive masked signs as having a [–IMG] value, indicating that lexically-encoded mouth gestures are assumed to be absent unless the mouth is fully visible. Progressive blurring of the face had no effect on sign identification accuracy for IMGs. This suggests that the eyebrows do not contribute in any substantial way to IMG perception, and that the mouth is the sole articulator for these contrastive mouth movements. During masked signing, participants went out of their way to avoid [+IMG] signs. The following chapter will show how MOUTH MORPHEMES differ from INHERENT MOUTH GESTURES in this respect. Since IMGs require the mouth, face masks elicit one specific interpretation in perception and force alternative communication strategies in production. MOUTH MORPHEMES, on the other hand, contain secondary features that become more prominent in masked signing and keep the MM intact without the need for any kind of avoidance strategy.
MOUTH MORPHEMES: Phonologization, feature type-shifting, and sign change

This chapter investigates the effects of masks on the interpretation and use of MOUTH MORPHEMES, the mouth movements that carry adjectival and adverbial information, and intensify descriptions of referents. Intensifying MMs are shown to consist of more than mouth movements alone; corresponding eyebrow and body movements were important secondary cues for MM perception and production. The presence of a mask also substantially decreased the likelihood of an intensified interpretation, even when the MM was articulated behind the mask. In production tasks, masked signers tended to map the corresponding eyebrow and body movements for MMs onto the specified HANDSHAPES for classifiers. This suggests a process of phonologization wherein the secondary (redundant) eyebrow and body cues for MMs become primary cues, due to the obstruction of the mouth. In the concluding discussion, I propose an analysis that blends the Hand-Tier and Prosodic Models to account for the transfer of secondary MM cues onto classifiers. Sign change directionality is discussed, and MMs are briefly assessed through the lens of the Dispersion Theory-based notions of articulatory effort and maximized perceptual contrast.

6.1 Perception of MOUTH MORPHEMES

Recall that participants viewed a variety of MOUTH MORPHEME stimuli, with the signer engaging different components of the MM (section 3.3.3). In some cases the signer was masked and used the corresponding eyebrow and body movements of the MM. Other times, the signer was unmasked, and used only the mouth component of the MM, but not the eyebrows or body. All possible combinations of mouth, eyebrow, and body engagement were accounted for in order to determine the perceptual weight of each cue – that is, which of the three MOUTH MORPHEME features have the greatest influence on the interpretation of the modified adjective or adverb.

Figure 6.1, which plots the proportion of intensified responses for each of the combinations of features (mouth movement, body movement, eyebrow movement) that were used across stimuli, reveals a few interesting results which we will pull apart further, one by one:
First, there was a major difference in the proportion of intensified responses for masked and unmasked stimuli. The presence of a mask (which entails the absence of a mouth movement) prevented the proportion of intensified responses from reaching higher than about 35%, even when both the eyebrows and body were engaged (Figure 6.1). The absence of a mask (which, given the structure of the experiment, entails the presence of a mouth movement), ensured that participants would get an intensified reading at least 55% of the time, even if neither the eyebrows or body were engaged. The statistically significant difference in the proportion of overall intensified responses across mask conditions is shown in Figure 6.2. Here, the left bar represents the collective grouping of the three leftmost bars of Figure 6.1, and the right bar represents the collective grouping of the four rightmost bars of Figure 6.1.

Another notable result shown in this figure is the difference between the proportion bars for [+Mask +Body +Brows] and [–Mask –Body –Brows]. When the body and eyebrows were engaged in an intensifying manner, but the signer was wearing a mask, participants were still less likely to get an intensified reading than when the only indication of intensity was the mouth gesture (with no eyebrow or body engagement). This challenges hypothesis MM H1 (see p. 39), and supports the notion that the mouth carries the majority of the intensifying

<table>
<thead>
<tr>
<th></th>
<th>Proportion of intensified responses</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mask</td>
<td>20.7%</td>
<td>-16.38</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>No mask</td>
<td>73.9%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Fig. 6.2: Proportion of intensified responses across mask condition
“content” in the MOUTH MORPHEME “package.” The mouth appears to be the most salient intensifying feature, though the body and eyebrows are clearly still important, otherwise we would expect to see an equal proportion of intensified responses for [–Mask –Body –Brows], [–Mask +Body –Brows], and [–Mask –Body +Brows].

Figure 6.1 also reveals that the proportion of intensified responses is very similar between [+Body –Brows] and [–Body +Brows] conditions, within either mask condition; the first and second bars are close together, and the fifth and sixth bars are close together. Within the +Mask condition, trading off between using either only the body or only the eyebrows did not result in a significant difference in the proportion of intensified responses:

<table>
<thead>
<tr>
<th>Condition</th>
<th>Proportion intensified</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>+Mask +Body –Brows</td>
<td>9.6%</td>
<td>-1.99</td>
<td>.09</td>
</tr>
<tr>
<td>+Mask –Body +Brows</td>
<td>18.2%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Also within the +Mask condition, stimuli that engaged both the body and the eyebrows had a significantly higher proportion of intensified responses than the group of masked stimuli that engaged either only the body or only the eyebrows:

<table>
<thead>
<tr>
<th>Condition</th>
<th>Proportion intensified</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>+Mask, only body or only eyebrows</td>
<td>14.4%</td>
<td>-3.62</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>+Mask, both body and eyebrows</td>
<td>33.3%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The same patterns held for unmasked stimuli; there was no significant difference in proportion of intensified responses between stimuli that engaged only the eyebrows and stimuli that engaged only the body, but there was a significant difference between the group of stimuli that engaged either only the body or only the eyebrows, and stimuli that engaged both:

<table>
<thead>
<tr>
<th>Condition</th>
<th>Proportion intensified</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>–Mask +Body –Brows</td>
<td>72.4%</td>
<td>0.30</td>
<td>.76</td>
</tr>
<tr>
<td>–Mask –Body +Brows</td>
<td>70.5%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Condition</th>
<th>Proportion intensified</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>–Mask, only body or only eyebrows</td>
<td>71.4%</td>
<td>-6.34</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>–Mask, both body and eyebrows</td>
<td>95.2%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Figure 6.3 below illustrates that for both masked and unmasked stimuli, there was a significant difference between stimuli that used just one of the two secondary MM cues, and stimuli that used both:

This result suggests that the eyebrow and body movements which co-occur with MM mouth movements are roughly equally important components of the MM. Deleting one and substituting the other did not significantly change how often participants interpreted the intensity of the descriptions in the stimuli. However, when both body movements and eyebrow movements were added together, there was a significant increase in the likelihood of an intensified interpretation, compared to only having one of the two.

We can see, based on our observations thus far, that while the mouth movement is the most influential and essential component of the MM, the corresponding body and eyebrow movements also play an important role. The “total MM package” must include both the primary and secondary cues.

### 6.1.1 Mixed effects model for intensified responses

A mixed effects model determined the significance of each tested predictor on the likelihood of an intensified response. The strongest model included mask condition, body condition, and brow condition as fixed effects. “Participant” was included as a random effect.

$$
\text{glmer(ad}\$\text{Intensified} \sim \text{Mask\_Condition} + \text{Body\_Cond} + \text{Brow\_Cond} + (1|\text{ParticipantID}), \\
data = \text{ad, family = binomial})
$$
All fixed effects were significant predictors of the likelihood of an intensified response. The intercept coefficient represents the log odds of an intensified response when the reference levels of the model are met (no mouth movement, no body movements, no eyebrow movements). When these reference levels are met, the odds of getting an intensified response are only 0.05 to 1. It is nearly 20 times more likely to observe an intensified response by changing the mask condition from “Mask” to “No Mask” for stimuli without body or eyebrow movements. Adding body movement to the reference level conditions increases the likelihood of an intensified reading by a factor of three, and adding eyebrow movements to the reference level conditions multiplies this likelihood by about 3.7.

### 6.2 Production of MOUTH MORPHEMES

In keeping with the trend of spotlighting the production results that directly relate to perception findings, this section will focus on a production phenomenon related to eyebrow and nonmanual body movements that was broadly observed for both Deaf and non-Deaf participants. As demonstrated in the previous section, the corresponding eyebrow and body movements for MOUTH MORPHEMES were salient cues of intensification to the extent that participants often interpreted adverbs and adjectives as intensified even when the signer was masked, as long as the eyebrows and body were engaged.

In production, when participants were masked – and thus unable to use the mouth components of MMs – they tended to temporally extend the eyebrow and nonmanual body movements of the MM onto the sign that referred back to whichever entity had originally been modified by the adjective or adverb. Figure 6.4 below shows the general sequence of actions for unmasked and masked adverb, when the intensifying mouth morpheme was used to intensify an adjective:
Unmasked signers generally introduced the noun (Sign A) before describing it with an intensified adjective (Sign B). When referring back to the noun denoted by Sign A (typically using a classifier construction), signers did not apply any mouth, eyebrow, or nonmanual body movements to the referring sign (Sign C). Masked signing, however, produced a different result. In this case, since the mouth was obstructed, the adjective (Sign B') was intensified by the eyebrows and nonmanual body movements that corresponded to the MOUTH MORPHEME we would have seen had the mouth been visible. Any time a classifier (Sign C') was used to refer back to the noun denoted by Sign A, this classifier took on the eyebrow and body movement properties of the adjectival MOUTH MORPHEME (Sign B'). The same process occurred for intensified adverbs, though this action sequence (Figure 6.5) looks slightly different because verbs are articulated simultaneously with their intensified adverbs:

**Figure 6.4:** Sequence of events for MOUTH MORPHEME production (adjectives)

**Figure 6.5:** Sequence of events for MOUTH MORPHEME production (adverbs)
The stimulus item in Figure 6.6 below elicited particularly illustrative examples of this mapping of eyebrow and body articulations from MOUTH MORPHEMES onto classifier constructions during masked signing:

**Figure 6.6:** Stimulus item designed to elicit OOO, MM and CHA MOUTH MORPHEMES

The three coffee cups in the picture are identical in their design, and differ only in size. Participants tended to use the OOO, MM, and CHA MOUTH MORPHEMES when describing the coffee cups sequentially. In unmasked signing, classifier HANDSHAPES were used to refer back to the established noun without any mouth movements. The photo sequence below shows an example of a description of the large coffee cup on the right. COFFEE CUP (Sign A) establishes the referent. In Sign B, the signer describes the referent as extremely large, combining the adjective LARGE with an intensifying MOUTH MORPHEME (CHA). The rest of the phrase consists of an iconic tracing of the cup’s design using the G-HANDSHAPE classifier (Sign C). During the articulation of the classifier, the signing space and eyebrows are neutral:

Contrastively, classifier constructions in masked signing were coarticulated with the eyebrow and body articulations from the preceding MOUTH MORPHEME, as shown below.
In this case, the signer uses the G-HANDSHAPE classifier to trace the shape on the coffee cup, while maintaining a raised eyebrow position and widened signing space. Two additional examples are provided below, with side-by-side comparisons of classifier constructions in unmasked and masked signing. The two photos below show WHOLE-ENTITY CLASSIFIER (WECL) constructions representing a small, elderly woman walking up a mountain. The OOO MOUTH MORPHEME, used to intensify the description of the woman’s tiny frame, consists of a primary mouth feature along with the secondary features of furrowed eyebrows and a contracted signing space. In (a), the WECL is articulated normally, with a 1-HANDSHAPE and no eyebrow or body features. In (b), the classifier is coarticulated with the secondary eyebrow and body features for OOO.

Another example is given on the next page, this time with the CLENCH MOUTH MORPHEME, which intensifies a description of two objects that are close to one another in space; the meaning shifts from “x and y are close” to “x and y are extremely close.” This sequence was elicited via a video stimulus item that showed an airplane stunt with two planes coming within a few feet of crashing together. The “adjective” image on the left shows the intensified sign for CLOSE as it was articulated in both unmasked and masked signing. In (a), the two airplanes are shown flying near each other with two WECLs formed with Y-HANDSHAPES on both hands. In (b), these WECLs are coarticulated with the secondary features of CLENCH; the signer shrinks her signing space slightly, leans forward, and furrows her brows.
Crucially, the brow and body positions were singularly-specified in each of the modified classifier constructions illustrated above; they remained constant throughout the entire articulation of the classifier phrase, rather than changing specifications in sync with the manual movements. Many more classifier modifications like these were produced by participants, regardless of hearing status.

6.3 Discussion

Based on the behavior described in this chapter, it is safe to say that signers were aware of the fact that their interlocutor could not see their face, and adjusted their MOUTH MORPHEME production accordingly. There is a key difference, then, between the effect of face masks on MOUTH MORPHEMES and INHERENT MOUTH GESTURES. Masked signing forced participants to avoid [+IMG] signs altogether, because IMGs are encoded into lexical items and require the mouth articulation. MOUTH MORPHEMES, on the other hand, were articulable and perceivable across mask conditions, because they contain non-mouth cues that can become more prominent and signal the meaning of the MM even when the mouth is blocked.

Eyebrow and body movements are perhaps best labeled as secondary cues in these intensified constructions due to their supporting role in the realization of MOUTH MORPHEMES. As shown in section 6.1, the presence of the mouth in MMs is the surest way to get an intensified reading, but these secondary articulations do a fairly good job of communicating the same meaning without the mouth, if need be. In the following discussion, I propose an analysis of the brow and body transfer phenomenon wherein the secondary cues for MOUTH MORPHEMES are phonologized when the mouth is unavailable, resulting in classifier forms that use redundant cues as contrastive features. The Hand-Tier and Prosodic Models are blended to explain the transfer of NMMs from the timing-specified PROSODIC FEATURES node of adjectives and adverbs to the singularly-specified INHERENT FEATURES node for classifier constructions. This process is additionally discussed in the context of the Dispersion Theory-oriented notion that surface forms are expected to reflect a balance between minimizing the articulatory effort required to produce them, and maximizing their perceptual distinctiveness.
6.3.1 Phonologization

In spoken language, listeners are “sensitive to the multiple phonetic cues that contribute to distinguishing sound categories,” even those that are simply natural physical consequences of the execution of the primary cue (Winter & Wedel 2016: 507). These contributing intrinsic phonetic properties of sound segments or sequences can be encoded into the phonology of a language. This process, called phonologization, occurs when secondary or redundant cues organically assume contrastive (phonemic) status over time (Hyman 2013: 3-4).

Phonologization may be catalyzed by misperception on the part of the listener. Ohala (1981) emphasized that speakers of a language are also listeners of that language, and that in cases of misperception, the listener is the true source of sound change. A listener may misperceive an “incomplete or ambiguous acoustic signal,” incorrectly parsing the linguistic intentions of the speaker. This misperception is then reflected in the speech of the “listener-turned-speaker” (Johnson et al. 2007: 530).

Nasalization in French is one notable example of a sound change driven by phonologization. In Standard Modern French, nasality is contrastive on vowels; /ɛ/, /ɛ̃/, /ɔ/, and /ɔ̃/ are all phonemic segments. This contrast, which emerged from a process of regressive assimilation and consonant elision, illustrates how redundant phonetic cues can become phonemic. In Old French, coda nasal consonants were realized, and the preceding oral vowels were regressively nasalized as a natural consequence of anticipatorily lowering the velum during the production of the vowel. During this period, French oral and nasal vowels were allophonic, just as they are in Modern English. The Middle French period “[presented] a period of variability in the quality of the vowel and the realization of the nasal consonant,” until eventually coda nasal consonants were no longer realized (Terry & Webb 2013: 155). Nasality was retained in the pre-nasal vowels, and became a contrastive vowel feature.

<table>
<thead>
<tr>
<th>Old French</th>
<th>Middle French</th>
<th>Standard Modern French</th>
</tr>
</thead>
<tbody>
<tr>
<td>ũN</td>
<td>ũ(N)</td>
<td>ũ</td>
</tr>
<tr>
<td>vend ‘sell-3G’</td>
<td>[vʌn]</td>
<td>[vʌ(ŋ)]</td>
</tr>
<tr>
<td>vin ‘wine’</td>
<td>[vɛn]</td>
<td>[vɛ(ŋ)]</td>
</tr>
<tr>
<td>maison ‘house’</td>
<td>[mæj.zɔn]</td>
<td>[mɛ.zɔ(ŋ)]</td>
</tr>
</tbody>
</table>

Table 6.2: Diachronic sound change in French (adapted from Terry & Webb 2013)

\[
\begin{array}{c}
C \quad ũ \quad C \\
\Downarrow \\
[+\text{nasal}] 
\end{array} \rightarrow \begin{array}{c}
C \quad ũ 
\end{array}
\]

Figure 6.7: Emergence of contrastive vowel nasality
Figure 6.7 above diagrams the association of the [nasal] feature from the coda consonant to the preceding vowel, resulting in the phonemic encoding of vowel nasality.

Some cases of tonogenesis – the emergence of tonal contrast – have also been attributed to phonologization. In many Athabaskan languages, syllables contrast for high vs. low tone. In the case of Gwich’in, phonologization of tone developed from an earlier contrast between syllables with and without glottalization (realized as creaky voice) in Proto-Dene (Michaud & Sands 2020: 37). Creaky voice (marked with a tilde below the vowel) is a non-modal phonation type that requires the vocal folds to vibrate at a lower rate. The natural byproduct – lower pitch, or F0 – shifted diachronically from a redundant phonetic cue to a contrastive phonemic feature. Thus, modal voice syllables in Proto-Dene became high tone syllables in Gwich’in, and creaky voice syllables became low tone syllables. Table 6.3 and Figure 6.8 depict this process.

<table>
<thead>
<tr>
<th>Proto-Dene</th>
<th>Gwich’in</th>
</tr>
</thead>
<tbody>
<tr>
<td>smoke</td>
<td>ḥád</td>
</tr>
<tr>
<td>belly</td>
<td>wɔʈ</td>
</tr>
</tbody>
</table>

Table 6.3: Tonogenesis in Gwich’in (adapted from Michaud & Sands 2020)

Figure 6.8: Emergence of contrastive tone

Phonologization has been the source of many more instances of sound change, including contrastive palatalization in Russian (Padgett 2003), i-umlaut in West Germanic (Dresher 2016), and the current incipient development of tone in Phnom Penh Khmer (Kirby 2014).

6.3.2 Merging two models of ASL phonology

Now, we consider phonologization in the context of the brow and body “transfer” phenomenon described in section 6.2. Figures 6.7 and 6.8 share a key structural similarity with the Hand-Tier diagrams of ASL compound formation in section 2.1.1. In both schemata, a dotted line represents the transfer of a particular feature from one deleted segment to an adjacent segment. We will borrow this element of the Hand-Tier Model to account for the transfer of MOUTH MORPHEME “fragments” (the secondary, redundant articulations made by the eyebrows and body) from modified adjectives or adverbs to classifier structures. Brentari’s Prosodic Model will also prove useful in this analysis, as it allows us to distinguish between singularly-specified INHERENT FEATURE NMMs and timing-specified PROSODIC FEATURE NMMs.
Assuming the view that MOUTH MORPHEMES are bundles of features including mouth, eyebrow, and body movements, phonologization of redundant articulations occurs when the primary articulator (the mouth) is blocked. Eyebrow and body features that correspond to the mouth component of a given MOUTH MORPHEME transfer over to the referential classifier, becoming the new primary cues that represent, for example, the intensification of adjectives or adverbs that relate to the referent.

6.3.2.1 Timing relations and PROSODIC → INHERENT feature conversion

There is an added detail to this process that requires the Prosodic Model. All observed MOUTH MORPHEMES have a specific temporal relationship with the manual movements of whichever sign they modify. For example, the OOO, MM, and CHA MOUTH MORPHEMES from our coffee cup example are all articulated in sync with the timing-specified PROSODIC FEATURES for SMALL, MEDIUM, and TALL, respectively. MOUTH MORPHEMES are therefore prosodic features that occupy the otherwise vacant NMM node on the PF branch of the modified sign:

![Figure 6.9: Timing relations for mouth, eyebrow, and body features in CHA](image)

When eyebrow and body specifications move over to classifier constructions, they no longer have a timing specification; the eyebrow and body features remain consistent across the entire articulation of the classifier, and are thus singularly-specified. Eyebrow movements remain in the same position (e.g. raised), and body specifications become a general MANNER of articulation that maps onto every path movement in the articulation of the classifier. These too are INHERENT FEATURES with no timing specification.
6.3.2.2 Why classifiers?

Though secondary articulations were attached to non-classifier referring signs in a few cases, this phenomenon was primarily observed with classifier constructions. Classifiers are probably the only element of ASL grammar that have been more egregiously neglected in the ASL literature than NONMANUAL MARKERS. Nonetheless, there seems to be a broad consensus that these constructions are used in most sign languages to maximize morpheme count while minimizing syllable count. Compared to signs from the non-native lexicon and core lexicon, they are free to use a virtually endless variety of path movements and settings, as long as the specified hand configuration is kept intact. Since classifiers are only specified for HANDSHAPE, they are by definition non-contrastive segments. Their primary function is to act as a template onto which PATH, SETTING, and ORIENTATION information is imposed, depending on the characteristics of the classifier’s referent.

![Figure 6.10: Transformation of redundant MM articulations from PROSODIC to INHERENT FEATURES](image)

Essentially, classifiers only truly contain INHERENT FEATURES, and a minimal set at that. There are no specified timing relations for classifier constructions by default, because the classifier is represented by HANDSHAPE alone; PROSODIC FEATURES are “filled in” based on the specific use case. The PROSODIC FEATURE side of the classifier structure is an empty canvas onto which signers can project a wide range of timing-specified elements. In masked signing, MOUTH MORPHEME fragments from the PROSODIC FEATURE set of a given sign are forced to move somewhere new. The mouth is no longer visible, so eyebrow and body positions are left to transfer over to classifier structures, where there is an open NMM slot on the INHERENT FEATURES side. These MOUTH MORPHEME fragments become INHERENT FEATURES of the classifier which are specified only once, and remain in the same position along with the singularly-specified HANDSHAPE, regardless of how the signer moves the hand in space.

6.3.3 Unidirectional vs. bidirectional sound change

In many cases, related phonetic phenomena can drive phonologization in one direction or the other, depending on which element was phonemic from the start. For example, the relationship between vowel length and F0 contour has the potential to change the status of either property from phonetic to phonemic. In languages with contrastive vowel length, listeners’ reinterpretation of a phonetically redundant falling tone on long vowels as phonemic
can result in tonal contrast. Likewise, languages with contrastive tone can develop a vowel length contrast as a result of listeners' reinterpretation in the opposite direction. The sound change is therefore bidirectional; it can occur in either direction depending on which property starts out as phonemic.

On the other hand, some sound changes are unidirectional; contrastive vowel length has been shown to develop into contrastive vowel height, but not vice-versa (Lehner-LeHoullier 2013: 98). This bidirectional-unidirectional asymmetry is due to listeners' sensitivity to redundant cues based on whether or not the cue co-occurs systematically with the corresponding contrastive property in their native language. Cues which have an impact on the perception of a contrastive element for all speakers (regardless of their language background) are “intrinsically associated.” An intrinsically associated cue is more tightly associated with the contrastive element than an “extrinsically associated” cue that only has an impact on perception for speakers of a language in which the redundant and phonemic cues co-occur systematically. Bidirectionality in sound change is only allowed for extrinsically associated cues.

In the perception portion of this experiment, there was no discernible split between Deaf and non-Deaf participants with regards to their perception of intensifying mouth morphemes based on redundant eyebrow and body movement cues. These cues thus appear to be intrinsically associated, at least in the results for this experiment (i.e. they have an impact on the perception of contrastive elements regardless of participants’ language background). This apparent unidirectionality could simply be a result of this particular experiment’s design, so I will stop short of making the claim that redundant MOUTH MORPHEME cues are in fact intrinsically associated. However, it is useful to consider sign change directionality, at least as a hypothetical, to imagine how ASL might change diachronically if masks were to be mandated long enough for the mouth to lose its status as an important articulator.

It may be the case that, while redundant eyebrow and body cues can usurp mouth movements as the primary features for MOUTH MORPHEMES, the opposite change would not be allowed. That is, if ASL were instead a language that phonemically encoded eyebrow and body movements as intensifying morphemes with redundant mouth cues, we would not expect to ever see a diachronic loss of eyebrow and body movements, with mouth movements remaining as the sole phonemic property of face-based intensifiers. Figure 6.1 from section 6.1 reflects this, because the proportion of intensified responses was substantially lower for signs that only used the mouth than for signs that used either the eyebrows, body, or both. In other words, so-called “MOUTH MORPHEMES” are probably better labeled as NONMANUAL MORPHEMES; the intensified meaning is not carried solely by the shape and movement of the mouth. Instead, the mouth, eyebrows, and nonmanual body parts cooperate to modify adjectives and adverbs.

6.3.4 Articulatory effort and perceptual distinctiveness

The results presented in this chapter open up richer opportunities for reasoning about the role of the face as an additional articulatory system that complements the hands in sign
languages. In the Dispersion Theory framework, languages select phonological contrasts based on three “functional goals” (Padgett 2003; Flemming 2004):

1. Maximize the distinctiveness of contrasts.
2. Minimize articulatory effort.
3. Maximize the number of contrasts.

Effective communication thus relies on the ability of speakers to maintain perceptually salient contrasts for the listener’s sake, while minimizing the biomechanical forces involved in the articulation of speech segments, for their own sake (Kirchner 1998). Articulatory effort has been studied as a potential driving force behind some phonological processes in sign languages, and as a factor that helps shape sign language lexicons (Napoli, Sanders & Wright 2014; Sanders & Napoli 2016; Napoli & Liapis 2019). However, these discussions typically focus on the difference in mobility and contractile speed of the muscles and joints at the most and least distal points of the limbs (e.g. the fingers vs. the shoulders). The articulatory effort involved in facial movements has yet to be considered in relation to manual movements.

Eyebrow and mouth movements certainly require less physical effort than, for instance, rotating the arm in space using the shoulder, or moving the hands and forearms by changing the angle of the elbow. The systematic adjustments that masked participants made for MOUTH MORPHEME production suggests that in ASL, the face helps distribute articulatory effort across the body, and that perceptual distinctiveness is achieved through the combination of manual and nonmanual movements. When the mouth was available, participants were able to describe a tall person walking by simply using the low-effort CHA MOUTH MORPHEME, and then demonstrating the walking motion by lightly bouncing the 1-HANDSHAPE classifier through neutral space. In masked signing, participants expressed the same meaning by transferring the secondary feature of widened signing space (with larger, more exaggerated arm movements) onto the classifier construction. In order to maintain and maximize the distinctiveness of the intensified description of the referent, participants sacrificed some articulatory ease when they could not use their mouths. I will further explore perceptual distinctiveness and the interaction between low- and high-effort motor movements of the limbs and face in a future paper to be completed this year.

6.4 Summary

In this chapter, I provided evidence for bundles of primary and secondary features that contribute to the full articulation and perception of MOUTH MORPHEMES. The presence of a face mask was the most reliable predictor of getting an intensified interpretation, but co-occurring eyebrow and body movements were also important. Participants were more likely to interpret descriptions with a higher number of MOUTH MORPHEME features as intensified. In production, secondary articulations of the eyebrows and body were amplified and phonologized, mapped onto classifier constructions, and transformed from PROSODIC to INHERENT FEATURES. Classifiers, which are only specified for a subset of INHERENT FEATURES, are prime candidates for absorbing redundant MOUTH MORPHEME cues because they always
have an empty NMM node on the INHERENT FEATURE side of the structure. Ultimately, the most important distinction is between IMGs and MMs. While IMGs are lexically-encoded and cannot be perceived or produced in masked signing, MMs consist of more than just the mouth and can spread their secondary features onto other constructions.
Conclusion and further research

In this paper, I have demonstrated first and foremost that face masks do indeed have a significant effect on the production and perception of signs in American Sign Language (ASL). By obstructing the mouth and observing different results for each of the three mouth movement types in question, we arrive at a better understanding of the structure of NONMANUAL MARKERS and the different roles that SPOKEN LANGUAGE MOUTHINGS, INHERENT MOUTH GESTURES, and MOUTH MORPHEMES play in ASL grammar.

SPOKEN LANGUAGE MOUTHINGS (SLMs) are certainly the least consequential mouth movement type, as they are optional and rooted in the phonology of another language. However, perception results for SLMs showed that these forms, which echo the phonology of spoken language, aid in comprehension to differing degrees based on the hearing status of the watcher. Non-Deaf participants made substantially greater use of SLMs than Deaf participants during perception tasks, indicating a potential bilingual activation phenomenon wherein ASL-English bilinguals can identify a sign in the former language faster if it is coarticulated with a mouthed component from the latter language. Hearing status also factored into differences in the structures of SLMs during production; non-Deaf signers tended to mouth entire words, while Deaf signers mostly mouthed single syllables and segments that involve more anterior (i.e. visually salient) portions of the mouth. Overall, the obstruction of the mouth for SLMs explained more about the different tendencies of ASL users themselves, rather than about the architecture of the language.

There are a few potential future research topics involving SLMs that could further elucidate their purpose in sign languages as well as the mind’s facility for multisensory integration. First of all, a comparative analysis of sign languages separated by SLM frequency would be appropriate and novel. SLMs are not as prevalent in all sign languages as they are in ASL. Even more, many sign languages – like the previously-discussed Ugandan Sign Language (UgSL) – borrow mouthed forms from a variety of languages based on historical relation, prestige, and geographic adjacency (Lutalo-Kiingi 2014). It would be useful to have a clearer picture of the sociolinguistic factors that contribute to which languages are selected for mouthing, and for which specific areas of the lexicon.

Multisensory integration is another topic to which SLMs closely relate. One could imagine an experiment that targets an effect similar to the one described in McGurk & MacDonald (1976), but with signs rather than spoken segments. It may be the case that ASL-English bilinguals (or signed-spoken bilinguals more generally) prioritize one language over the other during perception when faced with two types of conflicting visual signals (mouthed words and manually-articulated signs).
INHERENT MOUTH GESTURES (IMGs) and MOUTH MORPHEMES (MMs) yielded intriguing and revelatory results in both perception and production tasks. IMGs are generally assumed to be unspecified when one’s interlocutor is masked; participants overwhelmingly interpreted masked signs that belonged to an IMG-based minimal pair as [–IMG]. Put simply, for IMGs, if the mouth is not visible, you assume it isn’t moving. This assumption was clearly mirrored during production tasks. During masked signing, instead of making adjustments to [+IMG] signs in order to ensure that the interlocutor understood which sign was intended, participants avoided them altogether. They tended to settle for somewhat cumbersome alternative communicative strategies that involved arduous circumlocution and clunky grammar. This confirms that IMGs truly are encoded into the phonology of a small set of lexemes to the extent that articulating a [+IMG] sign without using the mouth is entirely out of the question.

MOUTH MORPHEMES, on the other hand, continued to be perceived and produced during masked signing, albeit with some systematic adjustments made by watchers and signers. In perception, participants picked up on the eyebrow and body movements that tend to co-occur with MMs, and often still interpreted masked signs as having a MOUTH MORPHEME as long as these extra gestures were present. Production tasks revealed that eyebrow and body movements are in fact redundant cues that buttress the articulation of the MM, which is driven by the primary mouth articulation.

Classifier constructions, which are only specified for HANDSHAPE, absorbed secondary eyebrow and body movements in a phonologization process that allowed the MM’s meaning to come through even though the mouth was blocked. Mouth, eyebrow, and body articulations constitute a timing-specified bundle of PROSODIC FEATURES, coordinated with the manual articulations of adjectives or adverbs. They become singularly-specified INHERENT FEATURES when they map onto classifier constructions. MOUTH MORPHEMES are thus more flexible than INHERENT MOUTH GESTURES in the presence of face masks; they are still articulable, but signers must adapt their habits of perception and production in order to continue using them.

Of the three types of mouth movements investigated in this paper, MOUTH MORPHEMES are the ripest for future experimental sign language research. Having established that secondary visual cues become more prominent when primary cues are dampened (just as in spoken language), future experiments may test whether a similar process occurs when other sign parameters are inhibited for whatever reason. For example, if a signer’s fingers are less nimble than the average person’s due to injury, cold hands, or a motor disorder, perhaps secondary HANDSHAPE cues at less distal points of the limbs (e.g. the elbows or shoulders) would undergo phonologization and become primary contrastive elements.

The process of writing this paper has made it abundantly clear to me that, while much of the material that one learns in a linguistics undergraduate program is transferrable from spoken to signed languages, analyzing the VISUAL-SPATIAL modality requires a very different toolbox and a radical shift in thinking. My hope is that mainstream linguistics education continues to move in a direction that better accounts for all communication systems. Spoken languages are undeniably prioritized in every subfield. If we hope to capture what is really going on in the phonology, syntax, morphology, and semantics of human...
communication, we need to pay closer attention to sign languages, even when they present problems for established theory and received wisdom in the field.
## Appendices

### Appendix A: Production stimulus inventory

<table>
<thead>
<tr>
<th>Type</th>
<th>Name</th>
<th>Source</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Storyboard</td>
<td><em>The Wind and the Sun</em></td>
<td>PinkFong! Kids’ Songs &amp; Stories</td>
<td>Participants clicked through captioned screenshots from the video. After reading through the story, the same images were shown sequentially without captions, and participants signed the story back to me.</td>
</tr>
<tr>
<td>Storyboard</td>
<td><em>The Tortoise and the Hare</em></td>
<td>PinkFong! Kids’ Songs &amp; Stories</td>
<td>Same as above.</td>
</tr>
<tr>
<td>Picture description</td>
<td>Close cars</td>
<td>Dropbox link</td>
<td>Two cars parked close together</td>
</tr>
<tr>
<td>Picture description</td>
<td>Coffee</td>
<td>Dropbox link</td>
<td>Three coffee cups of different sizes, with elaborate designs</td>
</tr>
<tr>
<td>Picture description</td>
<td>Duchess</td>
<td>Dropbox link</td>
<td>Duchess character from Cartoon Network’s <em>Foster’s Home for Imaginary Friends</em></td>
</tr>
<tr>
<td>Picture description</td>
<td>Farm</td>
<td>Dropbox link</td>
<td>Cartoon drawing of a farm and hills</td>
</tr>
<tr>
<td>Picture description</td>
<td>Dogs #1</td>
<td>Dropbox link</td>
<td>Four dogs of different sizes and breeds</td>
</tr>
<tr>
<td>Picture description</td>
<td>Dogs #2</td>
<td>Dropbox link</td>
<td>Two small dogs of different breeds on an elaborate bed spread</td>
</tr>
<tr>
<td>Picture description</td>
<td>Giant</td>
<td>Dropbox link</td>
<td>Cartoon drawing of a giant standing in front of a small character, holding a NO TRESPASSING sign</td>
</tr>
<tr>
<td>Picture description</td>
<td>Lizard</td>
<td>Dropbox link</td>
<td>A green gecko on a leaf</td>
</tr>
<tr>
<td>Picture description</td>
<td>Peacock</td>
<td>Dropbox link</td>
<td>Cartoon drawing of a colorful peacock, with three angry crows sneering at him</td>
</tr>
<tr>
<td>Picture description</td>
<td>Study</td>
<td>Dropbox link</td>
<td>Three students studying in focused, stressed, and careless manners, respectively</td>
</tr>
</tbody>
</table>

81
Wilt and Eduardo characters from Cartoon Network’s "Foster’s Home for Imaginary Friends"
Cartoon drawing of a Thanksgiving spread with turkey, potatoes, fruit, etc.
Two airplanes nearly crashing
MLB player Jim Edmonds making a diving catch in center field
Animation of a blue character tossing a guitar into the air and catching it
Animation of stick figure hikers ascending a mountain, with a small, frail old woman straggling behind
Clip from the animated movie "Olive the Other Reindeer," in which a dog guides Santa’s sleigh with reindeer
Football fans rushing the field at the end of a game
Animation of a fat leopard sleeping and falling off of a tree branch
Animation of a large, strong lumberjack walking through a forest while a little girl skips alongside him
Animation of the Pink Panther character disturbing a beehive
Animation of an anthropomorphic tornado forcing a cat to fly off of a tree
MLB player Vladimir Guerrero throwing a runner out from right field
Animation of a thin character squatting with a barbell
Whale breaching water surface
Rock band Phish jumping on trampolines

The grocery store is right next to my house, but the hospital is very far away from my house.
Appendix B: R script for SLM perception

##### Mouthing data

```r
md = read.csv("/Users/joshuacelli/Desktop/SLM_DATA.csv", header = TRUE, sep=",")
```

# This task was not designed to measure correct answers, since all signs used in the stimuli were sufficiently different to the extent that we can assume no questions would be missed. Only 0.035% of questions were answered incorrectly. These were removed. Correct vs. incorrect answers will be relevant in the section on minimal pairs, but not for this section on mouthing redundancy.

---

Sentence translation

John’s handwriting is sloppy, because he is careless and lazy when he writes. My handwriting is perfect, because I am careful and focused when I write.

Mary, John, and Alex were sitting on a boat, fishing. Mary was focused, and watching the fish very closely. John was relaxed, sitting back comfortably, waiting for the fish to come. Alex wasn’t paying any attention, and was staring at the sky and daydreaming.

Sentence translation

I have a ton of food on my plate, John has a normal amount of food on his plate, and Mary has a tiny bit of food on her plate.

Sentence translation

The drunk man walked through a crowd of people, stumbling around. All the people stared at him in shock.

One day, I was driving carelessly down the road, singing along to loud music. I was driving way too fast, and swerving across the lanes! Suddenly, I saw police lights behind me, and a cop pulled me over. Now, I always drive carefully and slowly.

Sentence translation

I should work because I need money.

Sentence translation

The student is late to class.

Sentence translation

The girl bought a lottery ticket every day. She was successful today.

Sentence translation

If you don’t have money, you should work.

Sentence translation

I should study because I have a test tomorrow.

Sentence translation

The girl bought a lottery ticket every day. She was finally successful today.

Sentence translation

The student is late to class, and she hasn’t done her homework yet.

Sentence translation

The girl bought a lottery ticket every day. She finally won today.

Sentence translation

I need to study because I have a test tomorrow.

Sentence translation

If you don’t have money, you must work.

Sentence translation

The student is not in class yet.
# Renaming column for response time:
names(md)[11] <- "ResponseTime"

##### Plotting overall response time:
```r
ggplot(md, aes(x=ResponseTime, fill=)) +
  geom_density(alpha=0.5)
```

# Some response times were extremely long relative to the others.
# Adding a log transformation column for response times:
```r
log(md$ResponseTime) -> md$logRT
```

# There is a datapoint way off to the right that needs to be excluded.
# Trying outlier exclusion:
```r
md[which(md$logRT > quantile(md$logRT, .25, na.rm=TRUE) - 3*IQR(md$logRT) &
    md$logRT < quantile(md$logRT, .75) + 3*IQR(md$logRT)),] ->
  md_excluded
```

```r
quantile(as.numeric(md$logRT), probs=c(.25, .75), na.rm = TRUE)
```
```
  25%  75%
  6.530844  7.323774
```
```r
Q <- quantile(md$logRT, probs=c(.25, .75), na.rm = TRUE)
iqr <- IQR(md$logRT, na.rm=TRUE)
up <- Q[2]+1.5*iqr # Upper Range
low<- Q[1]-1.5*iqr # Lower Range
md_excluded<- subset(md, md$logRT > (Q[1] - 1.5*iqr) & md$logRT < (Q[2]+1.5*iqr))
```

# This drops us from 3122 to 3048 variables.
```r
1-(3048/3122)
```
```
  = 0.02370275
```

# Only .02% of the data was excluded.

##### Plotting overall logRT:
```r
ggplot(md_excluded, aes(x=logRT, fill=)) +
  geom_density(alpha=0.5)
```

# The distribution looks normal now, for response times overall.
# We will start out by visualizing response times for different conditions.
# First, we look at the effect of the mask condition overall.
# Adding a factor column for MaskCondition:
```r
md_excluded$"Mask_Condition" <- "Mask"
md_excluded$Mask_Condition[md_excluded$MaskCondition == 0] <- "No mask"
```

# Plotting:
```r
j <- ggplot(md_excluded, aes(x=logRT, fill=Mask_Condition)) +
  geom_density(alpha=0.5) +
  xlab("log Response Time") +
  theme_classic()+
  theme(text = element_text(family="LM Roman Demi 10")+)
  guides(fill=guide_legend(title = "Mask Condition"))
```

# There is a peak at a lower response time for stimuli with no mask.
# We will run an F-test to compare the variances of these normal distributions:
```r
var.test(md_excluded[which(md_excluded$Mask_Condition == "Mask"),]$logRT,
  md_excluded[which(md_excluded$Mask_Condition == "No mask"),]$logRT)
F test to compare two variances

data:  md_excluded[which(md_excluded$Mask_Condition == "Mask"), ]$logRT and md_excluded[which(md_excluded$Mask_Condition == "No mask"), ]$logRT
F = 1.1603, num df = 764, denom df = 2282, p-value = 0.01063
alternative hypothesis: true ratio of variances is not equal to 1
95 percent confidence interval:
 1.035027 1.305099
sample estimates:
 ratio of variances
 1.160274

# Difference of variance is statistically significant. p-value = 0.01063

##### Visualizing logRT by word type (fingerspelled loanwords, lexicalized fingerspelled word, core lexicon sign):

ggplot(md_excluded, aes(x=TargetWordType, y=logRT, fill = TargetWordType)) +
xlab("Target Word Type") +
 ylab("log Response Time") +
scale_x_discrete(labels=c("Core sign", "Lexicalized FS", "FS loanword")) +
 theme_bw()+
theme(text   = element_text(family="LM Roman Demi 10")) +
guides(fill=guide_legend(title = "Target Word Type")) +
gg_violin() + ylim(4,10)

# The distributions across the different target word types are very similar, though fingerspelled loanwords have a slightly wider distribution, while core and lexicalized fingerspelled signs have a tighter distribution.

##### Visualizing logRT by whether or not the target word was mouthed:

md_excluded["Mouthing_Grouped"] <- "Mouthing"
md_excluded$Mouthing_Grouped[md_excluded$Mouthing == "none"] <- "No mouthing"
md_excluded$Mouthing_Grouped[md_excluded$Mouthing == "mask"] <- "No mouthing"

# Creating a new column to convert the categorical mouthing variables of "none", "target", "all", and "mask" to 0, 1, 2, and 0, respectively.
# The reason for this is because the amount of mouthing increases with each mouthing level, so I'll want to see it as a continuous factor.

md_excluded["Mouthing_Num"] <- 0
md_excluded$Mouthing_Num[md_excluded$Mouthing_Grouped == "Mouthing"] <- 1

# Creating a new dataframe with just non-masked stimuli:

md_unmasked = md_excluded[which(md_excluded$Mask_Condition=="No mask"), ]
md_unmasked$Mouthing_Grouped <- relevel(md_unmasked$Mouthing_Grouped, ref = "No mouthing")

# Plotting response time by mouthing level (for unmasked stimuli):

ggplot(md_unmasked, aes(x=logRT, fill=Mouthing_Grouped)) +
 geom_density(alpha=0.5) +
 xlab("log Response Time") +
guides(fill=guide_legend(title = "Mouthing Condition"))+
 theme_classic()+
theme(text   = element_text(family="LM Roman Demi 10"))

# At first glance, this graph is not very informative.

##### Adding an interaction between word type and mouthing, to see whether mouthing effects the different word types differently.

ggplot(md_unmasked, aes(x=interaction(Mouthing_Grouped, TargetWordType), y=(logRT.),)) +
 theme_linedraw()+
 theme(text   = element_text(family="LM Roman Demi 10"))+
xlab("Interaction between Mouthing and Target word type") +
ylab("log Response Time")+
 geom_boxplot(notch=TRUE) + ylim(4.5,9) +
# This graph is informative.
# For all word types, mouthing had a negative effect on response time, but the effect was most
# extreme for fingerspelled loanwords.

##### Blurriness

# First, we'll look to see whether there is an overall correlation of face blurriness on
response time.

ggplot(md_excluded, aes(x=Blurriness, y=logRT)) +
  geom_point() + geom_smooth(method = lm)

# Jittering the data to remove the tie warning:
BlurJit <- jitter(md_excluded$Blurriness)
BlurLRT <- jitter(md_excluded$logRT)

# Replotting:

ggplot(md_excluded, aes(x=BlurJit, y=logRT)) +
  xlab("Blurriness") +
  theme_gray() +
  theme_text = element_text(family="LM Roman Demi 10") +
  geom_point(alpha=0.3) + geom_smooth(method = lm)

# Correlation test:
Pearsons product-moment correlation

data:  BlurJit and BlurLRT
t = 6.0396, df = 1727, p-value = 1.888e-09
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
  0.09733962 0.18967715
sample estimates:
cor
  0.1438214

# This is a statistically significant weak correlation, though we do see a slight increase in
response time as the face is progressively blurred.

# It will be useful to see whether response time changed differently for masked and unmasked
conditions:

ggplot(md_excluded, aes(x=BlurJit, y=logRT, color=Mask_Condition)) +
  theme_gray() +
  theme_text = element_text(family="LM Roman Demi 10") +
  xlab("Blurriness") +
  ylab("log Response time") +
  guides(fill=guideLegend(title = "Mask Condition")) +
  geom_point(alpha=0.3) + geom_smooth(method = lm)

# Response time increased for unmasked stimuli as the face was progressively blurred, where
response times for masked stimuli basically had no change as blurriness increased.

# This suggests that non-facial cues have no effect on the perception of redundant mouthing
gestures.
# For masked stimuli, the eyes and eyebrows are the only visible part of the face.
# We can take the slope of the red Mask line to represent the effect of blurring the eyes and
eyebrows alone (since the mouth is automatically blocked for masked stimuli).
# Blurring the eyes and eyebrows alone had no effect on how quickly participants identified
signs.
# Since mouthings are redundant and provide no lexical contrast or semantic meaning, they are
completely separable from all additional facial cues.
# Given this result, we will focus on the difference between the mouthed and unmouthed
condition for redundant mouthings in the following steps. Since in this experiment, "mask"
entails "no mouthing."
### Overall participant responses to mouthing:

#### Creating a DeafFactor column:

```r
md_excluded$DeafFactor[md_excluded$HardHearing==1] <- "Hard-of-hearing"
md_excluded$DeafFactor[md_excluded$HardHearing==0 & md_excluded$Deaf==0] <- "Hearing"
```

#### Plot:

Boxplot needs to be reordered, so manually relabeling ParticipantID by number, making Deaf participants part of the same group in the plot:

```r
md_excluded$palp[md_excluded$ParticipantID == "p102"] <- "a"
md_excluded$palp[md_excluded$ParticipantID == "p103"] <- "b"
md_excluded$palp[md_excluded$ParticipantID == "p104"] <- "c"
md_excluded$palp[md_excluded$ParticipantID == "p105"] <- "d"
md_excluded$palp[md_excluded$ParticipantID == "p106"] <- "e"
md_excluded$palp[md_excluded$ParticipantID == "p107"] <- "f"
md_excluded$palp[md_excluded$ParticipantID == "p108"] <- "g"
md_excluded$palp[md_excluded$ParticipantID == "p109"] <- "h"
md_excluded$palp[md_excluded$ParticipantID == "p110"] <- "i"
md_excluded$palp[md_excluded$ParticipantID == "p111"] <- "j"
md_excluded$palp[md_excluded$ParticipantID == "p112"] <- "k"
md_excluded$palp[md_excluded$ParticipantID == "p113"] <- "l"
md_excluded$palp[md_excluded$ParticipantID == "p114"] <- "m"
md_excluded$palp[md_excluded$ParticipantID == "p115"] <- "n"
md_excluded$palp[md_excluded$ParticipantID == "p116"] <- "o"
md_excluded$palp[md_excluded$ParticipantID == "p117"] <- "p"
md_excluded$palp[md_excluded$ParticipantID == "p118"] <- "q"
md_excluded$palp[md_excluded$ParticipantID == "p119"] <- "r"
md_excluded$palp[md_excluded$ParticipantID == "p120"] <- "s"
md_excluded$palp[md_excluded$ParticipantID == "p121"] <- "t"
md_excluded$palp[md_excluded$ParticipantID == "p122"] <- "u"
md_excluded$palp[md_excluded$ParticipantID == "p123"] <- "v"
md_excluded$palp[md_excluded$ParticipantID == "p124"] <- "w"
md_excluded$palp[md_excluded$ParticipantID == "p125"] <- "x"
md_excluded$palp[md_excluded$ParticipantID == "p126"] <- "y"
md_excluded$palp[md_excluded$ParticipantID == "p127"] <- "z"

```r
ggplot(md_excluded, aes(x=interaction(Mouthing_Grouped, palp), y=(logRT), fill=DeafFactor)) +
  xlab("Response times across mouthing conditions for each participant") +
  ylab("log Response Time") +
  theme_minimal() +
  theme(text = element_text(family="LM Roman Demi 10")) +
  geom_boxplot(notch=TRUE) +
  guides(fill=guide_legend(title = "Hearing Status")) +
  theme_minimal() +
  theme(text = element_text(family="LM Roman Demi 10")) +
  geom_boxplot(notch=TRUE) +
  ylim(6.8) +
  theme(axis.text.x=element_blank(),
        axis.ticks.x=element_blank())
```

### Difference in response time across mouthing conditions for Deaf and Hearing groups

Now we'll group Deaf and non-Deaf participants into two Hearing Status groups, and plot their response times across mouthing conditions:

```r
md_excluded$DeafBin[md_excluded$Deaf == 0] <- "b"
```

```r
ggplot(md_excluded, aes(x=interaction(Mouthing_Grouped, DeafBin), y=(logRT),)) +
  xlab("Differences in response time across mouthing conditions by Hearing Status") +
  theme_minimal() +
  theme(text = element_text(family="LM Roman Demi 10")) +
  geom_boxplot(notch=TRUE) +
  ylim(6.8) +
  scale_x_discrete(labels=c("Deaf +M", "Deaf -M", "NonDeaf +M", "NonDeaf -M", "HoH +M", "HoH -M"))
```

### Breaking up the non-Deaf group into Hearing and HoH:

```r
ggplot(md_excluded, aes(x=interaction(Mouthing_Grouped, DeafFactor), y=(logRT),)) +
  xlab("Differences in response time across mouthing conditions by Hearing Status") +
  theme_minimal() +
  theme(text = element_text(family="LM Roman Demi 10")) +
  geom_boxplot(notch=TRUE) +
  ylim(6.8) +
  scale_x_discrete(labels=c("Deaf +M", "Deaf -M", "Hearing +M", "Hearing -M", "HoH +M", "HoH -M"))
```

We'll run a T-test to compare the mean log response times for mouthed and unmouthed conditions, for each group:
# Creating separate dataframes for Deaf and non-deaf participants:

df_Deaf = df_excluded[which(df_excluded$DeafBin=="a"),]
df_Hearing = df_excluded[which(df_excluded$DeafBin=="b"),]

# Mouthed and unmouthed mean log response times for Deaf participants:
t.test(df_Deaf[which(df_Deaf$Mouthing_Grouped == "Mouthing"),]$logRT,
df_Deaf[which(df_Deaf$Mouthing_Grouped == "No mouthing"),]$logRT)

Welch Two Sample t-test
data:  df_Deaf[which(df_Deaf$Mouthing_Grouped == "Mouthing"), ]$logRT and
df_Deaf[which(df_Deaf$Mouthing_Grouped == "No mouthing"), ]$logRT
t = -0.1696, df = 1532.3, p-value = 0.8653
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
  -0.05087140  0.04277429
sample estimates:
mean of x  mean of y
6.910188  6.914236

# Mouthed and unmouthed mean log response times for Hearing participants:
t.test(df_Hearing[which(df_Hearing$Mouthing_Grouped == "Mouthing"),]$logRT,
df_Hearing[which(df_Hearing$Mouthing_Grouped == "No mouthing"),]$logRT)

Welch Two Sample t-test
data:  df_Hearing[which(df_Hearing$Mouthing_Grouped == "Mouthing"), ]$logRT and
df_Hearing[which(df_Hearing$Mouthing_Grouped == "No mouthing"), ]$logRT
t = -11.008, df = 1507, p-value < 2.2e-16
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
  -0.4010707 -0.2797499
sample estimates:
mean of x  mean of y
6.77306   7.11347

##### Mixed effects model:

# Now, we'll run the mixed effects model, testing which factors best predict response time.
# Response time is a continuous variable, so we will use the lmer command in R.
# Releveling the mouthing and HearingStatus variables to "No mouthing" and "Deaf," respectively:

df_excluded$Mouthing_Grouped <- factor(df_excluded$Mouthing_Grouped, ordered=FALSE)
df_excluded$Mouthing_Grouped <- relevel(df_excluded$Mouthing_Grouped, ref = "No mouthing")
df_excluded$DeafFactor <- factor(df_excluded$DeafFactor, ordered=FALSE)
df_excluded$DeafFactor <- relevel(df_excluded$DeafFactor, ref = "Deaf")

###
m1 = (lmer(df_excluded$logRT ~ Trial.Number + Mouthing_Grouped +
(1|ParticipantID)+(1|TargetWord), data=df_excluded, REML=FALSE))

# This model failed to converge.

m3 = (lmer(df_excluded$logRT ~ Trial.Number + Mouthing_Grouped + TargetWordType+ Blurriness+
(1|ParticipantID)+(1|TargetWord), data=df_excluded, REML=FALSE))

summary(m3)

Linear mixed model fit by maximum likelihood ['lmerMod']
Formula: df_excluded$logRT ~ Trial.Number + Mouthing_Grouped + TargetWordType +
Blurriness + (1 | ParticipantID) + (1 | TargetWord)
Data: df_excluded
AIC  BIC logLik deviance df.resid
4356.9  4411.1   -2169.5     4338.9     3039

Scaled residuals:
Min  Q1      Median  Q3      Max
-3.0519  -0.6106  -0.0287  0.6359  3.5559

Random effects:
Groups   Name        Variance  Std.Dev.
ParticipantID (Intercept) 0.0495280 0.2225
TargetWord    (Intercept) 0.0009076 0.0266
Residual                  0.2380397 0.4879
Number of obs: 3048, groups: ParticipantID, 16; TargetWord, 6

Fixed effects:
   Estimate Std. Error t value
(Intercept)           6.923 0.0669 103.47
Trial.Number           -0.002 0.0003 -5.415
Mouthing_GroupedMouthing -0.178 0.018 -10.03
TargetWordTypeFSlex    0.078 0.034   2.26
TargetWordTypeFSloan   0.156 0.034  4.55
Blurriness             0.040 0.049   0.86

Correlation of Fixed Effects:
                      (Intr) Trial.Nm Mouthing_Grouped Trial.Wrd_TypeFSlex Trial.Wrd_TypeFSloan
Trial.Nm             -0.270
Mouthing_Grouped     -0.150  0.070
Trial.Wrd_TypeFSlex  -0.253 -0.013  0.000
Trial.Wrd_TypeFSloan -0.239 -0.062 -0.003  0.499
Blurriness           -0.326  0.125  0.007  0.000 -0.009

# Trying without TrialNumber as fixed effect:

m4 = (lmer(md_excluded$logRT ~ Mouthing_Grouped + TargetWordType + Blurriness +
          (1|ParticipantID)+(1|TargetWord), data=md_excluded, REML=FALSE))

summary(m4)

Linear mixed model fit by maximum likelihood 'lmerMod'
Formula: md_excluded$logRT ~ Mouthing_Grouped + TargetWordType + Blurriness +
          (1 | ParticipantID) + (1 | TargetWord)
Data: md_excluded

AIC  BIC logLik deviance df.resid
4384.0 4432.2  -2184.0   4368.0 3040

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.0866 -0.6176 -0.0419  0.6312  3.5499

Random effects:
Groups   Name         Variance  Std.Dev.
ParticipantID (Intercept) 0.0495 0.2225
TargetWord    (Intercept) 0.0009 0.0266
Residual                  0.240 0.490
Number of obs: 3048, groups: ParticipantID, 16; TargetWord, 6

Fixed effects:
   Estimate Std. Error t value
(Intercept)           6.826 0.066 104.14
Mouthing_GroupedMouthing -0.171 0.018 -9.63
TargetWordTypeFSlex    0.075 0.034   2.20
TargetWordTypeFSloan   0.145 0.034  4.33
Blurriness             0.046 0.049   0.94

Correlation of Fixed Effects:
                      (Intr) Mouthing_Grouped TargetWordTypeFSlex TargetWordTypeFSloan Blurriness
Mouthing_Grouped     -0.135
TargetWordTypeFSlex  -0.292  0.001
TargetWordTypeFSloan -0.291  0.001  0.500
Blurriness           -0.303 -0.002  0.002 -0.001

# Model comparison:
anova(m4, m3)

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Data: md_excluded
Models:
  m4: md_excluded$logRT ~ Mouthing_Grouped + TargetWordType + Blurriness +
      (1 | ParticipantID) + (1 | TargetWord)
  m3: md_excluded$logRT ~ Trial.Number + Mouthing_Grouped + TargetWordType +
      Blurriness + (1 | ParticipantID) + (1 | TargetWord)
Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
  m4  8 4384.0 4432.2 -2184.0   4368.0
  m3  9 4356.9 4411.1 -2169.5   4338.9 29.065      1  6.998e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# Model 3 is significantly better.
# Adding random slope of mouthing by participant:
  m5 = lmer(md_excluded$logRT ~ Trial.Number + Mouthing_Grouped + TargetWordType+
             (1+Mouthing_Grouped|ParticipantID)+(1|TargetWord), data=md_excluded, REML=FALSE)
# This model failed to converge.
  m6 = lmer(md_excluded$logRT ~ Trial.Number + Mouthing_Grouped + TargetWordType+
             (1|TargetWord)+(1+Mouthing_Grouped|ParticipantID), data=md_excluded, REML=FALSE)
summary(m6)

Linear mixed model fit by maximum likelihood . t-tests use Satterthwaites method
[ 'lmerModLmerTest' ]
Formula: md_excluded$logRT ~ TrialNumber + Mouthing_Grouped + TargetWordType +
        (1 | TargetWord) + (1 + Mouthing_Grouped | ParticipantID)
Data: md_excluded

AIC    BIC   logLik deviance df.resid
2563.9 2618.5  -1272.0   2543.9     1719
Scaled residuals:
   Min      1Q  Median      3Q     Max
-4.1300 -0.6250 -0.0011  0.6662  4.4167
Random effects:
   Groups        Name                     Variance  Std.Dev. Corr
     ParticipantID (Intercept)              0.0510523 0.22595
     Mouthing_GroupedMouthing 0.0721615 0.26863  -0.36
     TargetWord    (Intercept)              0.0008245 0.02871
     Residual                               0.2462850 0.49627
Number of obs: 1729, groups:  ParticipantID, 9; TargetWord, 6

Fixed effects:
              Estimate Std. Error   df t value Pr(>|t|)
(Intercept)    7.433e+00  7.415e-02 1.225e+01  80.3 < 2e-16 ***
TrialNumber    -1.733e-03  6.366e-04 1.643e+03  -4.225 5.24e-05 ***
Mouthing_GroupedMouthing -3.15e-01  9.258e-02  9.001e+00  -3.991 0.000824 **
TargetWordTypeFSLex  1.442e-01  4.888e-02  5.078e+00   2.713  0.00994 *
TargetWordTypeFSLoan  1.699e-01  4.555e-02  5.136e+00   4.666  0.00055 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
     (Intr) TrlNmb Mth_GM TrgtWrdTypFSLx
TrialNumber    -0.246
Mouthing_GrpM   -0.354  0.016
TrgtWrdTypFSLx  -0.240 -0.015  0.000
TrgtWrdTypFSLn -0.224 -0.075 -0.001  0.500

# Comparing model 6 to model 3:
anova(m3,m6)

Data: md_excluded
Models:
  m3: md_excluded$logRT ~ TrialNumber + Mouthing_Grouped + TargetWordType +
      Blurriness + (1 | ParticipantID) + (1 | TargetWord)
m3: Blurriness + (1 | ParticipantID) + (1 | TargetWord)
m6: md_excluded$logRT ~ TrialNumber + Mouthing_Grouped + TargetWordType +
   (1 | ParticipantID) + (1 + Mouthing_Grouped | ParticipantID)

Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
m3  9  2620.4 2669.5 -1301.2   2602.4
m6 10  2563.9 2618.5 -1272.0   2543.9 58.524      1 2.009e-14 ***
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Model 6 is significantly better.

m7 = (lmer(md_excluded$logRT ~ Trial.Number + Mouthing_Grouped*DeafBin+
            (1|TargetWord)+(1+Mouthing_Grouped|ParticipantID), data=md_excluded, REML=FALSE))

# This model failed to converge.

m8 = (lmer(md_excluded$logRT ~ Trial.Number + Mouthing_Grouped*DeafBin+
            (1+Mouthing_Grouped|ParticipantID), data=md_excluded, REML=FALSE))

summary(m8)

Linear mixed model fit by maximum likelihood . t-tests use Satterthwaites method
['lmerModLmerTest']
Formula: md_excluded$logRT ~ TrialNumber + Mouthing_Grouped * DeafFactor +
            (1 + Mouthing_Grouped | ParticipantID)
Data: md_excluded

AIC      BIC   logLik deviance df.resid
2581.0   2630.1  -1281.5   2563.0     1720
Scaled residuals:
  Min      1Q  Median      3Q     Max
-3.8779 -0.6003 -0.0094  0.6332  4.3977

Random effects:
  Groups           Name        Variance Std.Dev. Corr
  ParticipantID   (Intercept) 0.03295  0.1815
  Mouthing_GroupedMouthing 0.01232  0.1110   0.53
  Residual                        0.25198  0.5020

Number of obs: 1729, groups: ParticipantID, 9

Fixed effects:
  Estimate Std. Error    df  t value Pr(>|t|)
  (Intercept)                  6.967e+00  9.685e-02 1.001e+01  71.939 6.47e-15 ***
  TrialNumber                  -1.568e-03  4.360e-04 1.711e+03  -3.597 0.000331 ***
  Mouthing_GroupedMouthing    -3.852e-02  6.628e-02  8.985e+00  -0.581 0.575351
  DeafFactorHearing           2.696e+00  1.265e+00  9.000e+00   2.130 0.034550 .
  Mouthing_GroupedMouthing:DeafFactorHearing -4.920e-01  8.891e-02  8.981e+00  -5.534 0.000367 ***

---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
  (Intr) TrlNmb Mth_GM DFFctH
  TrialNumber -0.227
  Mouthing_GrpM  0.310  0.827
  DeffcfrHrng -0.726  0.802 -0.242
  Mthn_GM:DFH -0.234 -0.006 -0.745  0.325

# Comparing model 8 to model 6:
anova(m6, m8)

Data: md_excluded
Models:
  m6: md_excluded$logRT ~ TrialNumber + Mouthing_Grouped + TargetWordType +
  m8: md_excluded$logRT ~ TrialNumber + Mouthing_Grouped * DeafFactor +

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```r
m6: (1 | TargetWord) + (1 + Mouthing_Grouped | ParticipantID)
Df AIC BIC logLik deviance Chisq Chi Df Pr(>Chisq)
m8  9 2581.0 2630.1 -1281.5   2563.0
m6 10 2563.9 2618.5 -1272.0   2543.9 19.072      1  1.259e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
# Model 6 is still significantly better.

# Trying without the random slope:
m9= (lmer(md_excluded$logRT ~ Trial.Number + Mouthing_Grouped + TargetWordType +
         (1 | TargetWord) + (1 | ParticipantID), data=md_excluded, REML=FALSE))
summary(m9)
Linear mixed model fit by maximum likelihood ['lmerMod']
Formula: md_excluded$logRT ~ Trial.Number + Mouthing_Grouped + DeafBin +
         (1 | TargetWord) + (1 | ParticipantID)
Data: md_excluded
AIC BIC logLik deviance df.resid
4386.9 4429.1 -2186.5  4372.9     3041
Scaled residuals:
     Min      1Q  Median      3Q     Max
-3.1383 -0.6047 -0.0293  0.6288  3.6172
Random effects:
Groups        Name        Variance Std.Dev.
ParticipantID (Intercept) 0.049884 0.22335
TargetWord    (Intercept) 0.005379 0.07334
Residual                  0.240066 0.48997
Number of obs: 3048, groups:  ParticipantID, 16; TargetWord, 6
Fixed effects:
                Estimate Std. Error t value
(Intercept)       7.0945355  0.0873961  81.177
Trial.Number      -0.0019358  0.0003267  -5.926
Mouthing_GroupedMouthing -0.1782617  0.0177948 -10.018
DeafBinb           0.0320277  0.1130759   0.283
Correlation of Fixed Effects:
                      (Intr) Trl.Nm Mth_GM
Trial.Numbr  -0.188
Mthng_GrpM    -0.115  0.070
DeafBinb     -0.647  0.000  0.001

# Comparing model 6 to model 9:
anova(m6, m9)
Data: md_excluded
Models:
  m9: md_excluded$logRT ~ TrialNumber + Mouthing_Grouped + DeafFactor +
  m6: md_excluded$logRT ~ TrialNumber + Mouthing_Grouped + TargetWordType +
  m6:     (1 | TargetWord) + (1 + Mouthing_Grouped | ParticipantID)
Df AIC BIC logLik deviance Chisq Chi Df Pr(>Chisq)
m9  7 2663.9 2702.1 -1324.9   2649.9
m6 10 2563.9 2618.5 -1272.0   2543.9 105.96      3  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
# Model 6 is the best model.

library("sjPlot")
plot_model(m6, type="re")
k <- plot_model(m6, type="re")
k + scale_color_sjplot()
```

Appendix C: R script for IMG perception

##### Minimal pair mouth gestures

# opening data
asd = read.csv("/Users/joshuacelli/Desktop/MinimalPairsDataQLNEW.csv", header = TRUE, sep=".")

##### First, we will look over response times.

# Duplicating reaction time column, with a new name:
names(asd)[14] <- "responsetime"

# Plotting the distribution of response times:

# There's a long tail, with a several tiny peaks at random points of very high response times.
# Right now I have 906 observations.
# Testing outlier exclusion:
asd[which(asd$responsetime > quantile(asd$responsetime, .25) - 3*IQR(asd$responsetime) & asd$responsetime < quantile(asd$responsetime, .75) + 3*IQR(asd$responsetime)),] ->
asdf

# The new dataframe has 893 observations.
1-(893/906)
[1] 0.01434879

# Only 1.4% of the data was excluded. We will go with this new dataframe moving forward.

# Plotting distribution of response times for the new dataframe:

# This looks somewhat normal, but it will still be good to do a log transformation because of the slightly odd shape.
# Creating a column for log response time:
log(asdf$responsetime) -> asdf$logRT

# Plotting distribution of log response time:

# Testing factors on response time

# Like with the mouthing dataset, we will start out by visualizing response times for different conditions.
# First, looking at the effect of the mask condition overall.
# Adding a factor column for MaskCondition:
asdf["Mask_Condition"] <- "Mask"
asdf$Mask_Condition[asdf$MaskCondition == 0] <- "No mask"

# Plotting:

The peaks look extremely similar. We'll set this condition aside for now, but this chart will be used in comparing minimal pair mouth gestures to redundant mouthings.

Now, just to make sure that there aren't any huge differences based on the minimal pair mouth gesture we were testing (of the three types), we'll visualize response time by mouth gesture used:

```r
ggplot(asdf, aes(x=MMUsed, y=logRT, fill = MMUsed)) +
  xlab("Mouth gesture tested") +
  ylab("log Response Time") +
  guides(fill=guide_legend(title = "Target Word Type")) +
  theme_bw() +
  geom_violin() + ylim(5,7)
```

These distributions actually look different. If we find any differences in response time across blurriness conditions and make a resulting mixed effects model, we would want to account for the mouth gesture used as a random effect.

### Blurriness

Again, we'll look to see whether there is an overall correlation of face blurriness on response time.

```r
ggplot(asdf, aes(x=Blurriness, y=logRT)) +
  geom_point() + geom_smooth(method = lm)
```

Jittering the data to block tie warning:

```r
BlurJit2 <- jitter(asdf$Blurriness)
BlurLRT2 <- jitter(asdf$logRT)
```

Replotting:

```r
ggplot(asdf, aes(x=BlurJit2, y=logRT)) +
  xlab("Blurriness") +
  geom_point(alpha=0.3) + geom_smooth(method = lm)
```

Correlation test

Pearsons product-moment correlation

```r
data:  BlurJit2 and BlurLRT2
t = 0.44813, df = 751, p-value = 0.6542
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
-0.05515991 0.08769374
sample estimates:
cor
0.01635035
```

There is no correlation at all.

It will still be useful to see whether response time changed differently for masked and unmasked conditions, in order to compare this effect to what we saw with mouthings:

```r
ggplot(asdf, aes(x=BlurJit2, y=logRT, color=Mask_Condition)) +
  xlab("Blurriness") +
  ylab("log Response time") +
  geom_point(alpha=0.3) + geom_smooth(method = lm) + ylim(5,7) +
  theme_bw()
```

Response time seems to be much less affected by blurriness and mask condition for minimal pair mouth gestures than for redundant mouthings.

Overall, we can see that minimal pair mouth gestures are unaffected by changes in face obfuscation relative to redundant mouthings.

This suggests that minimal pair mouth gestures are encoded as an inherent part of the lexical items for signs that use them, while the presence or absence of redundant mouthings have an effect on the amount of time it takes to process lexical items.
# For example, the difference between FINALLY and SUCCESS is the presence or absence of the
"pah" mouth gesture. Identifying the sign as SUCCESS or FINALLY based on the presence of "pah"
is akin to identifying, for example, FATHER vs. MOTHER, which differ only in the LOCATION
parameter.
# Because minimal pair mouth gestures are encoded into the phonology of lexical items in the
same way as handshape, location, movement, and palm orientation, differentiating between two
signs based on the non-manual signal parameter takes no additional mental processing time.
# However, as hypothesized, redundant mouthings have an effect on the mental processing time
for signs that have no inherent mouth movements, at least for Hearing participants.

######################################## Effects on Accuracy
# First, we will test the overall effect of the mask condition on accuracy:

# Making a Mask Condition non-numeric column:

asdf["Mask_Condition1"] <- "Mask"

asdf$Mask_Condition1[asdf$MaskCondition == 0] <- "No mask"

# Plotting:

ggplot(asdf) +
aes(x = Mask_Condition1, fill = factor(Correct)) + geom_bar(position = "fill") +
  xlab("Mask Condition") + ylab("Proportion of responses") +
  scale_fill_manual(name = "Accuracy", labels = c("Incorrect", "Correct"), values = c("purple4",
  "plum3")) +
  theme_classic()

# Overall, participants were had a far higher proportion of accurate responses for unmasked
stimuli than for masked stimuli.

# We'll run a t-test to compare the means:

t.test(asdf[which(asdf$MaskCondition == 1),]$Correct,
       asdf[which(asdf$MaskCondition == 0),]$Correct)

Welch Two Sample t-test
data:  asdf[which(asdf$MaskCondition == 1),]$Correct and asdf[which(asdf$MaskCondition == 0),]$Correct
t = -10.508, df = 890.91, p-value < 2.2e-16
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
  -0.3926756 -0.2690795
sample estimates:
  mean of x mean of y
  0.3744589 0.7053364

# The proportion of correct responses are significantly different across the mask condition
overall.

##### Blurriness and mask condition
# Now, we will plot the proportion of accurate responses by face blurriness, across mask
conditions.

ggplot(asdf, aes(x = Blurriness, y = Correct, colour = Mask_Condition1)) +
  stat_summary(fun.y = "mean", geom = "point", na.rm = TRUE) +
  ylab("Proportion of correct responses") +
  geom_smooth(method = lm, na.rm = TRUE) +
  theme_bw()

# There is little to no change in the proportion of accurate responses as the face is
progressively blurred for masked stimuli.
# For unmasked stimuli, however, there is a drastic effect of face blurriness on accuracy. As
the level of blurriness changes from completely clear to completely blurred, the proportion of
accurate responses essentially approaches chance.
This suggests that the visibility of the mouth is essential for identifying minimal pairs which are differentiated only by a mouth gesture, but also that the non-mouth facial cues (e.g. eyebrow movements) play no part in the identification of these minimal pair signs. We can take the red "Mask" line to represent the effect of obscuring parts of the face other than the mouth, since all masked stimuli have no mouth visibility by default. Thus, the manipulated variable for progressively-blurred masked stimuli is the visibility of non-mouth facial movements.

If non-mouth facial movements played a role in minimal pair sign identification, we would expect to see a decrease in accurate responses for masked stimuli as the face is progressively blurred. From this figure, we can see that accurate minimal pair sign identification relies on visibility of the mouth alone, but not on the rest of the face.

Testing Hearing Status for this chart:

Making a Mask Condition non-numeric column:

```r
asdf["DeafFactor"] <- "Hearing"
```

```r
asdf$DeafFactor[asdf$HearingStatus == 0] <- "Deaf"
```

We will make two separate graphs, one for Hearing, and one for Deaf participants:

Hearing participants:

```r
f <- ggplot(asdf[which(asdf$DeafFactor=="Hearing"),], aes(x = Blurriness, y = Correct, colour = Mask_Condition1)) +
  stat_summary(fun.y = "mean", geom = "point", na.rm = TRUE)+
  ylab("Proportion of correct responses") +
  ggtitle("Hearing group") +
  geom_smooth(method = lm, na.rm = TRUE) + theme(plot.title = element_text(hjust = 0.5))+
  theme_bw()
```

```r
f+coord_cartesian(ylim=c(0.2,1))
```

Deaf participants:

```r
g <- ggplot(asdf[which(asdf$DeafFactor=="Deaf"),], aes(x = Blurriness, y = Correct, colour = Mask_Condition1)) +
  stat_summary(fun.y = "mean", geom = "point", na.rm = TRUE)+
  ylab("Proportion of correct responses") +
  ggtitle("Deaf group") +
  geom_smooth(method = lm, na.rm = TRUE) + theme(plot.title = element_text(hjust = 0.5))+
  theme_bw()
```

```r
g+coord_cartesian(ylim=c(0.2,1))
```

These two plots show that the effect of blurriness on accuracy, across mask conditions, is virtually the same for Deaf and Hearing participants. While hearing status was a factor in the response times for redundant mouthings, it does not appear to play a role in correct sign identification for minimal pairs that differ in mouth gesture.

This provides evidence in support of the notion that signs with an inherent lexically-encoded mouth gesture are learned as a bundle of specified features, and thus Hearing individuals store these signs with their mouth gestures "attached" to the rest of the specified features.

Since the mouth gestures inherent to minimal pair signs have no relationship to spoken language, it is not surprising to see that Deaf and Hearing individuals react in the same way to their presence or absence, in contrast to the different reactions to redundant mouthings (which are related to spoken language) between these two groups.

It is also useful to see how this effect looks for each individual mouth gesture tested:

PAH:

```r
a <- ggplot(asdf[which(asdf$MMUsed=="pah"),], aes(x = Blurriness, y = Correct, colour = Mask_Condition1)) +
  stat_summary(fun.y = "mean", geom = "point", na.rm = TRUE)+
  ylab("Proportion of correct responses") +
  ggtitle("PAH") +
  theme_bw()+
  geom_smooth(method = lm, na.rm = TRUE) + theme(plot.title = element_text(hjust = 0.5))
```

```r
a+coord_cartesian(ylim=c(0.2,1.1))
```
# TH:

```r
b <- ggplot(asdf[which(asdf$MMUsed=="th"),]. aes(x = Blurriness, y = Correct, colour = Mask_Condition1)) +
  stat_summary(fun.y = "mean", geom = "point", na.rm = TRUE)+
  ylab("Proportion of correct responses") +
  ggtitle("TH")+
  theme_bw()+
  geom_smooth(method = lm, na.rm = TRUE) + theme(plot.title = element_text(hjust = 0.5))

b+coord_cartesian(ylim=c(0.2,1.1))
```

# SH/MUH

```r
c <- ggplot(asdf[which(asdf$MMUsed=="sh_muh"),]. aes(x = Blurriness, y = Correct, colour = Mask_Condition1)) +
  stat_summary(fun.y = "mean", geom = "point", na.rm = TRUE)+
  ylab("Proportion of correct responses") +
  ggtitle("SH/MUH") +
  theme_bw()+
  geom_smooth(method = lm, na.rm = TRUE) + theme(plot.title = element_text(hjust = 0.5))

c+coord_cartesian(ylim=c(0.2,1.1))
```

All three mouth gestures show a similar effect for accuracy; there are no major differences, where one particular mouth gesture was affected significantly less by blurriness and mask condition.

##### Testing the default understanding of minimal pair signs with a blocked non-manual signal.

# Now, we will test to see which of the signs in a minimal pair (or minimal triple) are chosen more often when the mouth is blocked.

# This will tell us whether a blocked parameter is assumed to be absent or present, and will open the door to additional research on blocked features for the other four parameters of ASL (but particularly handshape).

# First, plotting the overall proportion of Mouth Gesture sign selection across mask conditions:

```r
ggplot(asdf) +
  aes(x = Mask_Condition1, fill = factor(MMSelected)) + geom_bar(position = "fill") +
  xlab("Mask Condition") + ylab("Proportion of Mouth Gesture sign selection") +
  theme_bw()+
  scale_fill_manual(name = "Selected sign type", labels=c("No mouth gesture", "Mouth gesture"), values=c("purple4", "plum3"))
```

# This chart shows that for masked stimuli, the proportion of mouth gesture signs selected was lower than for unmasked stimuli.

# Running a t-test to compare the means:

```r
t.test(asdf[which(asdf$MaskCondition == 1),]$MMSelected, asdf[which(asdf$MaskCondition == 0),]$MMSelected)
```

Welch Two Sample t-test
data:  asdf[which(asdf$MaskCondition == 1),]$MMSelected and asdf[which(asdf$MaskCondition == 0),]$MMSelected
t = -7.7863, df = 882.29, p-value = 1.931e-14
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:  
-0.3158804 -0.1886947
sample estimates:  
mean of x mean of y
0.3463203 0.6186079

# There is a significant difference between the proportion of mouth gesture sign selection across mask conditions.

# Now, we will plot the effect of blurriness of the proportion of mouth gesture sign selection, across mask conditions:
ggplot(asdf. aes(x = Blurriness, y = MMSelected, colour = Mask_Condition1)) +
stat_summary(fun.y = "mean", geom = "point", na.rm = TRUE)+
ylab("Proportion of Mouth Gesture sign selection") +
geom_smooth(method = lm, na.rm = TRUE)+ theme(plot.title = element_text(hjust = 0.5))

# These figures indicate that when the face is obscured, participants tended to choose the
sign without a non-manual signal specification, over the sign with a non-manual signal
specification.
# This raises the question: If another parameter, such as handshape, is blocked, and
participants are to select between minimal pair signs that differ only in handshape, what are
the factors that would influence the choice of one sign over another? Would we find an effect
of lexical frequency, wherein the most commonly-used sign were selected? Or would it be
random?

# Again, it is useful to see the effect of which sign type was selected, for each of the three
mouth gestures tested:

# PAH:
d <- ggplot(asdf[which(asdf$MMUsed=="pah"),]. aes(x = Blurriness, y = MMSelected, colour =
Mask_Condition1)) +
stat_summary(fun.y = "mean", geom = "point", na.rm = TRUE)+
ylab("Proportion of Mouth Gesture sign selection") +
ggtitle("PAH") +
theme_bw()+
geom_smooth(method = lm, na.rm = TRUE) + theme(plot.title = element_text(hjust = 0.5))
d+coord_cartesian(ylim=c(0.0,1))

# TH:
e <- ggplot(asdf[which(asdf$MMUsed=="th"),]. aes(x = Blurriness, y = MMSelected, colour =
Mask_Condition1)) +
stat_summary(fun.y = "mean", geom = "point", na.rm = TRUE)+
ylab("Proportion of Mouth Gesture sign selection") +
ggtitle("TH") +
theme_bw()+
geom_smooth(method = lm, na.rm = TRUE) + theme(plot.title = element_text(hjust = 0.5))
e+coord_cartesian(ylim=c(0.0,1))

# SH/MUH:
f <- ggplot(asdf[which(asdf$MMUsed=="sh_muh"),]. aes(x = Blurriness, y = MMSelected, colour =
Mask_Condition1)) +
stat_summary(fun.y = "mean", geom = "point", na.rm = TRUE)+
ylab("Proportion of Mouth Gesture sign selection") +
ggtitle("SH/MUH") +
theme_bw()+
geom_smooth(method = lm, na.rm = TRUE) + theme(plot.title = element_text(hjust = 0.5))
f+coord_cartesian(ylim=c(0.0,1))

# TH and SH/MUH look quite similar, though the figure for PAH is slightly different.
# For PAH, there is a decrease in selection of FINALLY over SUCCESS for masked stimuli as the
face becomes progressively blurred.
# A potential explanation for this is that even when a signer is masked, the PAH mouth gesture
is somewhat visible because it involves a jaw movement downward. Perhaps participants noticed
this additional clue for masked non-blurred stimuli, and were looking for it as an indication
of the presence of the PAH mouth gesture for all masked stimuli. As the face became too
obscured to see any movement of the jaw, this additional cue was no longer visible and
participants were less likely to select the sign with the specified non-manual signal.

##### Mixed effects model for accuracy
# Now, we'll run mixed effects models for accuracy and mouth gesture sign selection.
# Both mixed effects models will use the glmer commands, because we are testing the odds of
observing the outcome of a categorical variable.
# We'll start with accuracy.
# Renaming the Trial.Number column, because the presence of a period was causing issues:
names(asdf)[9] <- "TrialNumber"
# Releveling Mask_Condition so that the reference level is "No mask."
```
asdf$Mask_Condition <- factor(asdf$Mask_Condition, ordered=FALSE)
asdf$Mask_Condition <- relevel(asdf$Mask_Condition, ref = "No mask")
```

# We will start with Blurriness, and Mask Condition as fixed effects, since we have seen
evidence of these two factors having an effect on accuracy.
# For random effects, we will use Participant to start, to capture the idiosyncratic
variability for participants.
```
e1 = glmer(Correct ~  Blurriness+Mask_Condition+(1|ParticipantID), data=asdf, family=binomial)
```

# Singular fit error. It appears that ParticipantID is not significant, and is causing the
singular fit error, as there is very little variance across these conditions for the
individual participants.
# We will try with MMUsed as a random effect, to capture idiosyncratic variability of word.
```
e2 = glmer(Correct ~  Blurriness+Mask_Condition+(1|MMUsed), data=asdf, family=binomial)
```
```
summary(e2)
```
```
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
Family: binomial  ( logit )
Formula: Correct ~ Blurriness + Mask_Condition + (1 | MMUsed)
Data: asdf

AIC      BIC   logLik deviance df.resid
931.8    950.3   -461.9    923.8      749

Scaled residuals:
Min      1Q  Median      3Q     Max
-2.2048 -0.8339  0.4719  0.6874  1.7468

Random effects:
Groups Name        Variance Std.Dev.
MMUsed (Intercept) 0.009287 0.09637

Number of obs: 753, groups:  MMUsed, 3

Fixed effects:
Estimate Std. Error z value Pr(>|z|)
(Intercept)         1.85878    0.24011   7.742 9.82e-15 ***
Blurriness         -0.34868    0.07156  -4.872 1.10e-06 ***
Mask_ConditionMask -1.51643    0.16256  -9.328  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
(Intr) Blrrns
Blurriness  -0.840
Mask_CondtnMs -0.496  0.169

# Blurriness and Mask_Condition are significant predictors of decrease in accuracy. It would
be good to have more variance explained by random effects.
# We will add Sentence as a random effect. MMUsed should be a crossed effect with Sentence,
because there is more than one sentence for each MMUsed.
```
e3 = glmer(Correct ~  Blurriness + Mask_Condition +  (1|Sentence) + (1|MMUsed), data=asdf, family=binomial)
```
```
# Singular fit error. I will test only Sentence instead, since there are two sentences for
each MMUsed, and thus Sentence as a random effect will also include variance explained by
MMUsed, to a degree. We will see which model is best.
```
e4 = glmer(Correct ~  Blurriness + Mask_Condition +  (1|Sentence) , data=asdf, family=binomial)
```
```
summary(e4)
```
```
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
Family: binomial  ( logit )
Formula: Correct ~ Blurriness + Mask_Condition + (1 | Sentence)
Data: asdf

AIC      BIC   logLik deviance df.resid
990.0    1010  -486.9    983.8      742

Scaled residuals:
Min      1Q  Median      3Q     Max
-2.2047 -0.8334  0.4721  0.6893  1.7464

Random effects:
Groups Name        Variance Std.Dev.
MMUsed (Intercept) 0.009287 0.09637
Sentence 0.000387 0.01968

Number of obs: 753, groups:  MMUsed, 3
Sentence, 2

Fixed effects:
Estimate Std. Error t value Pr(>|t|)
(Intercept)         1.85878    0.24011   7.742 9.82e-15 ***
Blurriness         -0.34868    0.07156  -4.872 1.10e-06 ***
Mask_ConditionMask -1.51643    0.16256  -9.328  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
(Intr) Blrrns
Blurriness  -0.840
Mask_CondtnMs -0.496  0.169

# Blurriness and Mask_Condition are significant predictors of decrease in accuracy. It would
be good to have more variance explained by random effects.
# We will add Sentence as a random effect. MMUsed should be a crossed effect with Sentence,
because there is more than one sentence for each MMUsed.
AIC      BIC   logLik deviance df.resid
924.6    943.1   -458.3    916.6      749

Scaled residuals:
          Min     1Q Median     3Q    Max
-2.3007 -0.8290  0.4346  0.7032  2.3431

Random effects:
Groups   Name        Variance Std.Dev.
Sentence (Intercept) 0.1166   0.3414
Number of obs: 753, groups: Sentence, 7

Fixed effects:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  1.9352     0.2732   7.082 1.42e-12 ***
Blurriness   -0.3742     0.0743  -5.039 4.68e-07 ***
Mask_ConditionMask -1.5492     0.1649  -9.397 < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
            (Intr) Blrrns
Blurriness  -0.759
Msk_CndtnMs -0.459  0.178

# Model comparison of e2 and e4:
anova(e2, e4)

Data: asdf
Models:
e2: Correct ~ Blurriness + Mask_Condition + (1 | MMUsed)
e4: Correct ~ Blurriness + Mask_Condition + (1 | Sentence)
Df  AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
e2  4 931.77 950.27 -461.89    923.77
e4  4 924.64 943.14 -458.32   916.64 7.1311      0  < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# e4 is the significantly better model.

# We will also try adding TrialNumber as a fixed effect to see whether there was any effect of accuracy as the session moved along:
e5 = glmer(Correct ~ TrialNumber + Blurriness + Mask_Condition + (1 | Sentence), data=asdf, family=binomial)
summary(e5)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
Family: binomial  ( logit )
Formula: Correct ~ TrialNumber + Blurriness + Mask_Condition + (1 | Sentence)
Data: asdf
AIC      BIC   logLik deviance df.resid
925.8    948.9   -457.9    915.8      748

Scaled residuals:
          Min     1Q Median     3Q    Max
-2.2913 -0.8375  0.4338  0.7008  2.2769

Random effects:
Groups   Name        Variance Std.Dev.
Sentence (Intercept) 0.1112   0.3334
Number of obs: 753, groups: Sentence, 7

Fixed effects:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  1.8034     0.3061   5.890 3.85e-09 ***
TrialNumber  0.0839     0.0834    1.016     0.310

100
Blurriness   -0.372311   0.074177  -5.019 5.19e-07 ***
Mask_ConditionMask -1.550821   0.164912  -9.404  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
(Intr) TrlNmb Blrrns
TrialNumber -0.461
Blurriness  -0.686  0.019
Msk_CndtnMs -0.397 -0.024  0.176

# TrialNumber is not a significant predictor of accuracy.
# Comparing model e4 and e5:

anova(e4,e5)

Data: asdf
Models:
  e4: Correct ~ Blurriness + Mask_Condition + (1 | Sentence)
  e5: Correct ~ TrialNumber + Blurriness + Mask_Condition + (1 | Sentence)
Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
e4  4 924.64 943.14 -458.32   916.64
e5  5 925.80 948.92 -457.90   915.80 0.8398      1     0.3595

# e4 is the better model.

# Lastly, we will test a model with an interaction between Blurriness and Mask_Condition:

e6 = glmer(Correct ~ Blurriness*Mask_Condition + (1|Sentence) , data=asdf, family=binomial)

summary(e6)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
Family: binomial  ( logit )
Formula: Correct ~ Blurriness * Mask_Condition + (1 | Sentence)
Data: asdf
AIC       BIC  logLik deviance df.resid
1036.9 1060.9   -513.5   1026.9      888

Scaled residuals:
  Min     1Q Median      3Q     Max
-5.3364 -0.7760  0.1874  1.0006  1.9326

Random effects:
  Groups   Name        Variance Std.Dev.
   Sentence (Intercept) 0.1652   0.4065

Number of obs: 893, groups:  Sentence, 7

Fixed effects:
     Estimate Std. Error   z value Pr(>|z|)
(Intercept) 4.1715     0.4683   8.907  < 2e-16 ***
Blurriness  -1.1388     0.1357  -8.391  < 2e-16 ***
Mask_ConditionMask -4.8912     0.5058  -9.670  < 2e-16 ***
Blurriness:Mask_ConditionMask  0.0091     0.1606   7.580 3.44e-14 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
(Intr) Blrrns Msk_CM
Blurriness  -0.906
Msk_CndtnMs  0.826  0.838
Blrrns:M_CM  0.765  0.838 -0.948

# Comparing model e6 to model e4:
anova(e4,e6)

Data: asdf
Models:
  e4: Correct ~ Blurriness + Mask_Condition + (1 | Sentence)
e6: Correct ~ Blurriness * Mask\_Condition + (1 | Sentence)

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</table>

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

# e6 is the significantly better model. We will use this mixed effects model.
# Explanation of this model:
# All fixed effects are statistically significant predictors of accuracy.
# The reference levels are met when Blurriness level is 0 and the stimuli is unmasked.
# The intercept estimate in this model describes the log odds of a correct response over an incorrect response when these reference levels are met.
# We can exponentiate this slope:
# \( \exp(4.41715) = 82.8598 \)
# The odds of a correct response over an incorrect response in this case is 83 to 1, though this is not a meaningful statement considering the fact that there is no way for the Blurriness level to be 0 (since a Blurriness level of 1 means that the stimuli was not blurred at all).
# Since Blurriness is a continuous factor, the coefficient here is a slope. Since we are looking at a glmer model, this coefficient represents a slope that shows us the change in odds of a correct response over an incorrect response with each increase of 1 in this factor, specifically for unmasked stimuli, in the given units (of Blurriness level).
# The Blurriness:Mask\_ConditionMask coefficient represents a slope that shows us the change in odds of a correct response with each increase of 1 in Blurriness level, for masked stimuli.
# We can exponentiate this slope:
# \( \exp(-1.1388) = 0.320203 \)
# In unmasked stimuli, for each increase of 1 unit of Blurriness level, the odds of a correct response are multiplied by 0.32.
# Therefore, the odds of a correct response decrease as the face is progressively blurred, for unmasked stimuli.

# The Blurriness:Mask\_ConditionMask coefficient represents a slope that shows us the change in odds of a correct response with each increase of 1 in Blurriness level, for masked stimuli.
# We can exponentiate this slope:
# \( \exp(0.0091) = 1.009142 \)
# In masked stimuli, for each increase of 1 in Blurriness level, the odds of a correct response are multiplied by 1.009142.
# The likelihood of a correct response actually increased slightly as the face was progressively blurred for masked stimuli.
# However, given the design of the experiment, it is likely that this increase in odds is due to chance, as we see that the overall proportion of correct responses for masked stimuli hovers around chance.
# The Mask\_ConditionMask coefficient represents the overall change in log odds of a correct response with respect to the reference level condition odds, when the mask condition is changed from “No mask” to “Mask.”
# We can exponentiate this slope:
# \( \exp(-4.8912) = 0.007512402 \)
# Overall, participants were far less likely to respond correctly to masked stimuli than to unmasked stimuli.

# Plotting the random effect of sentence:
plot_model(e6, type="re")
# This figure shows the by-sentence adjustment for the intercept, when the reference levels of the model are met. This is showing the odds of a correct response over a short response, for each individual sentence, when the reference levels are met.
# The odds are hovering around 1, which indicates that our fixed effects are probably capturing the result well.

##### Mixed effects model for Mouth Gesture sign selection
# Now, we will make a model that shows the predictions for a participant choosing the sign(s) with a specification for the non-manual signal, over the sign without a non-manual signal.
# We will start with Blurriness, and Mask Condition as fixed effects, since we have seen evidence of these two factors having an effect on accuracy.
# For random effects, we will use Participant to start, to capture the idiosyncratic variability for participants.
t1 = glmer(MMSelected ~ Blurriness+Mask_Condition+(1|ParticipantID), data=asdf, family=binomial)

summary(t1)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
Family: binomial ( logit )
Formula: MMSelected ~ Blurriness + Mask_Condition + (1 | ParticipantID)
Data: asdf

AIC      BIC   logLik deviance df.resid
926.6    945.1   -459.3    918.6      749

Scaled residuals:
Min      1Q  Median      3Q     Max
-2.9329 -0.7807 -0.4392  0.8498  2.4791

Random effects:
Groups        Name        Variance Std.Dev.
ParticipantID (Intercept) 0.4461   0.6679
Number of obs: 753, groups: ParticipantID, 9

Fixed effects:
Estimate Std. Error z value Pr(>|z|)
(Intercept)         1.15998    0.31654   3.665 0.000248 ***
Blurriness         -0.30087    0.07201  -4.178 2.94e-05 ***
Mask_ConditionMask -1.22472    0.16447  -7.446 9.60e-14 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
(Intr) Blrrns
Blurriness  -0.558
Mask_CondtnMs -0.324  0.125

# Adding Sentence as a random effect:
t2 = glmer(MMSelected ~ Blurriness+Mask_Condition+(1|ParticipantID) + (1|Sentence), data=asdf, family=binomial)

summary(t2)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
Family: binomial ( logit )
Formula: MMSelected ~ Blurriness + Mask_Condition + (1 | ParticipantID) + (1 | Sentence)
Data: asdf

AIC      BIC   logLik deviance df.resid
920.8    943.9   -455.4    910.8      748

Scaled residuals:
Min      1Q  Median      3Q     Max
-3.0448 -0.7395 -0.4265  0.8286  2.9068

Random effects:
Groups        Name        Variance Std.Dev.
ParticipantID (Intercept) 0.4837   0.6955
Sentence      (Intercept) 0.1327   0.3642
Number of obs: 753, groups: ParticipantID, 9; Sentence, 7

Fixed effects:
Estimate Std. Error z value Pr(>|z|)
(Intercept)         1.21611    0.35477   3.428 0.000608 ***
Blurriness         -0.32357    0.07447  -4.345 1.39e-05 ***
Mask_ConditionMask -1.27762    0.16875  -7.571 3.71e-14 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
(Intr) Blrrns
Blurriness  -0.558
Comparing model t1 to t2:

\[
\text{anova(t1,t2)}
\]

Data: asdf
Models:
t1: MMSelected ~ Blurriness + Mask_Condition + (1 | ParticipantID)
t2: MMSelected ~ Blurriness + Mask_Condition + (1 | ParticipantID) +
    (1 | Sentence)

<table>
<thead>
<tr>
<th></th>
<th>Df</th>
<th>AIC</th>
<th>BIC</th>
<th>logLik</th>
<th>deviance</th>
<th>Chisq</th>
<th>Chi Df</th>
<th>Pr(&gt;Chisq)</th>
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</thead>
<tbody>
<tr>
<td>t1</td>
<td>4</td>
<td>926.64</td>
<td>945.14</td>
<td>-459.32</td>
<td>918.64</td>
<td></td>
<td></td>
<td>1</td>
</tr>
<tr>
<td>t2</td>
<td>5</td>
<td>920.77</td>
<td>943.89</td>
<td>-455.38</td>
<td>910.77</td>
<td>7.8728</td>
<td>1</td>
<td>0.005018 **</td>
</tr>
</tbody>
</table>

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# t2 is a significantly better model.

# Adding TrialNumber as a fixed effect:

\[
\text{t3 = glmer(MMSelected ~ TrialNumber + Blurriness + Mask_Condition + (1|ParticipantID) + (1|Sentence), data=asdf, family=binomial)}
\]

summary(t3)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
Family: binomial (logit)
Formula: MMSelected ~ TrialNumber + Blurriness + Mask_Condition + (1 | ParticipantID) +
    (1 | Sentence)
Data: asdf

AIC   BIC logLik deviance df.resid
922.2 949.9 -455.1 910.2      747

Scaled residuals:
  Min    1Q  Median    3Q    Max
-3.0504 -0.7394 -0.4261  0.8284  2.8665

Random effects:
  Groups     Name        Variance Std.Dev.
  ParticipantID (Intercept) 0.4834   0.6953
  Sentence   (Intercept) 0.1255   0.3543

Number of obs: 753, groups:  ParticipantID, 9; Sentence, 7

Fixed effects:
  Estimate Std. Error    z value  Pr(>|z|)
(Intercept) 1.107422   0.381313    2.904     0.00368 **
TrialNumber -0.002588   0.003450   -0.750     0.45318
Blurriness  -0.322577   0.074445   -4.333    1.47e-05 ***
Mask_ConditionMask -1.279015   0.168833  -7.576    3.57e-14 ***

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
  (Intr) TrlNmb Blrrns
TrialNumber -0.376
Blurriness  -0.524  0.811
Msk_CndtnMs -0.275 -0.020  0.135

# Comparing model t3 to t2:

\[
\text{anova(t2,t3)}
\]

Data: asdf
Models:
t2: MMSelected ~ Blurriness + Mask_Condition + (1 | ParticipantID) +
    (1 | Sentence)
t3: MMSelected ~ TrialNumber + Blurriness + Mask_Condition + (1 | Sentence)
As with the Accuracy model, TrialNumber is not a significant fixed effect, and does not improve the model. We will not use it as a fixed effect.

# Adding an interaction between Blurriness and Mask_Condition:

t4 = glmer(MMSelected ~ Blurriness*Mask_Condition+(1|ParticipantID) + (1|Sentence),
data=asdf, family=binomial)

summary(t4)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
Family: binomial ( logit )
Formula: MMSelected ~ Blurriness * Mask_Condition + (1 | ParticipantID) + (1 | Sentence)
Data: asdf

AIC      BIC   logLik deviance df.resid
1076.4   1105.2   -532.2   1064.4      887

Scaled residuals:
    Min     1Q Median     3Q    Max
-2.9671 -0.7410 -0.4099  0.7720  2.7237

Random effects:
   Groups     Name        Variance Std.Dev.
   ParticipantID (Intercept) 0.4768   0.6905
   Sentence      (Intercept) 0.1747   0.4179

Number of obs: 893, groups: ParticipantID, 9; Sentence, 7

Fixed effects:
                 Estimate Std. Error z value Pr(>|z|)
(Intercept)                     1.8481     0.4086   4.523 6.09e-06 ***
Blurriness                     -0.5475     0.1016  -5.390 7.05e-08 ***
Mask_ConditionMask             -2.3561     0.3941  -5.978 2.26e-09 ***
Blurriness:Mask_ConditionMask   0.1191     0.1364   3.064  0.00218 **

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
    (Intr) Blrrns Msk_CM
Blurriness -0.676
Msk_CndtnMs -0.554  0.703
Blrrns:M_CM  0.497 -0.730 -0.918

# Comparing model t4 to t2:

anova(t4,t2)

Data: asdf
Models:
  t2: MMSelected ~ Blurriness + Mask_Condition + (1 | ParticipantID) +
  (1 | Sentence)
  t4: MMSelected ~ Blurriness * Mask_Condition + (1 | ParticipantID) +
  (1 | Sentence)

Df    AIC    BIC  logLik deviance  Chisq Chi Df Pr(>Chisq)
  t2  5 920.77 943.89 -455.38   910.77
  t4  6 922.21 949.95 -455.10   910.21 0.5614      1     0.4537

# t4 is the significantly better model. We will use this model for our analysis.
# All fixed effects are statistically significant predictors of choosing the Mouth Gesture sign.
# The reference levels are met when Blurriness level is 0 and the stimuli is unmasked.
# The intercept estimate in this model describes the log odds of a Mouth Gesture sign response
over an non-Mouth Gesture sign response when these reference levels are met.
\[ \exp(1.8481) = 6.35 \]

# The odds of a Mouth Gesture sign response in this case is 6.4 to 1, though this is not a meaningful statement considering the fact that there is no way for the Blurriness level to be 0 (since a Blurriness level of 1 means that the stimuli was not blurred at all).
# Since Blurriness is a continuous factor, the coefficient here is a slope. Since we are looking at a glmer model, this coefficient represents a slope that shows us the change in odds of a Mouth Gesture sign response with each increase of 1 in this factor, specifically for unmasked stimuli, in the given units (of Blurriness level).
# We can exponentiate this slope:
\[ \exp(-.5475) = 0.578394 \]
# In unmasked stimuli, for each increase of 1 unit of Blurriness level, the odds of a correct response are multiplied by 0.578.
# Therefore, the odds of a Mouth Gesture sign response decrease as the face is progressively blurred, for unmasked stimuli.

# The Blurriness:Mask_ConditionMask coefficient represents a slope that shows us the change in odds of a Mouth Gesture sign response with each increase of 1 in Blurriness level, for masked stimuli.
\[ \exp(0.1191) = 1.126483 \]
# In masked stimuli, for each increase of 1 in Blurriness level, the odds of a Mouth gesture sign response are multiplied by 1.126483
# The likelihood of a Mouth gesture sign response actually increased slightly as the face was progressively blurred for masked stimuli.

# The Mask_ConditionMask coefficient represents the overall change in log odds of a Mouth gesture sign response with respect to the reference level condition odds, when the mask condition is changed from "No mask" to "Mask."
\[ \exp(-2.2561) = 0.104 \]
# Overall, participants were less likely to respond correctly to masked stimuli than to unmasked stimuli.

# Plotting the random effect of sentence:
plot_model(t4, type="re")
# This figure shows the by-sentence adjustment for the intercept, when the reference levels of the model are met. This is showing the odds of a correct response over a short response, for each individual sentence, when the reference levels are met.
# The odds are hovering around 1, which indicates that our fixed effects are probably capturing the result well.

## Appendix D: R script for MM perception

##### Adverbs
# opening data
ad = read.csv("/Users/joshuacelli/Desktop/adverbsnew.csv", header = TRUE, sep=",")
# To start, we want to see what the proportion of "intensified" responses is for each of the combinations of features used.
# We'll add a column called "Interaction, with values for each of the intensifying features.

ad["Interaction"] <- "-Mask, +Body, +Brows"
ad$Interaction[ad$MM==1 & ad$Body==1 & ad$Eyebrows==1 & ad$MaskCondition==0] <- "-Mask +Body +Brows"
ad$Interaction[ad$MM==1 & ad$Body==1 & ad$Eyebrows==0 & ad$MaskCondition==0] <- "-Mask +Body -Brows"
ad$Interaction[ad$MM==1 & ad$Body==0 & ad$Eyebrows==1 & ad$MaskCondition==0] <- "-Mask -Body +Brows"
ad$Interaction[ad$MM==1 & ad$Body==0 & ad$Eyebrows==0 & ad$MaskCondition==0] <- "-Mask -Body -Brows"
ad$Interaction[ad$MM==0 & ad$Body==1 & ad$Eyebrows==1 & ad$MaskCondition==1] <- "+Mask +Body +Brows"
ad$Interaction[ad$MM==0 & ad$Body==1 & ad$Eyebrows==0 & ad$MaskCondition==1] <- "+Mask +Body -Brows"
ad$Interaction[ad$MM==0 & ad$Body==0 & ad$Eyebrows==1 & ad$MaskCondition==1] <- "+Mask -Body +Brows"
ad$Interaction[ad$MM==0 & ad$Body==0 & ad$Eyebrows==0 & ad$MaskCondition==1] <- "+Mask -Body -Brows"

# Not all these combinations are in the data, but I just added all the possible combinations so that I wouldn't miss any as I thought through it logically.
# Plotting the proportion of "Intensified" responses for all combinations:

ggplot(ad) +
aes(x = Interaction), fill = factor(Intensified)) + geom_bar(position = "fill") +
  xlab("Features used") + ylab("Proportion of responses") +
  scale_fill_manual(name = "Interpretation", labels=c("Neutral", "Intensified"),
  values=c("purple4", "plum3"))

# Reordering the levels of the factor to show increasing proportion of "Intensified" responses:

# Replotting:
ggplot(ad) +
aes(x = Interaction), fill = factor(Intensified)) + geom_bar(position = "fill") +
  xlab("Features used") + ylab("Proportion of responses") +
  theme_bw()+

# We will divide "masked" and "unmasked" stimuli into two groups, and compare their mean proportion of "Intensified" responses:
# Adding a non-numeric column for Mask Condition:
ad$Mask_Condition[ad$MaskCondition == 0] <- "No mask"

# Plotting the proportion of "Intensified" responses across mask conditions:
ggplot(ad) +
aes(x = Mask_Condition), fill = factor(Intensified)) + geom_bar(position = "fill") +
  xlab("Mask Condition") + ylab("Proportion of responses") +
  theme_bw()+
  scale_fill_manual(name = "Interpretation", labels=c("Neutral", "Intensified"),
  values=c("purple4", "plum3"))

# We will run a t-test to compare the means:
t.test(ad[which(ad$Mask_Condition == "Mask"),]$Intensified,
  ad[which(ad$Mask_Condition == "No mask"),]$Intensified)

Welch Two Sample t-test
data:  ad[which(ad$Mask_Condition == "Mask"), ]$Intensified and ad[which(ad$Mask_Condition == "No mask"), ]$Intensified
t = -16.381, df = 702.54, p-value < 2.2e-16
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-0.5806691 -0.4563764
sample estimates:
mean of x mean of y
0.2076677 0.7391905

# The means are significantly different. The mask condition has a significant effect on the proportion of "intensified" responses.
The second thing we notice about FIGURE [] is that the proportion of "Intensified" responses does not appear to be very different between [+Body -Brows] and [-Body +Brows] conditions, for either masked or unmasked stimuli.

However, there is a noticeable difference between these two conditions (if we view them as a group), and [+Body +Brows] conditions for both masked and unmasked stimuli.

We will run T-tests to compare means:

Comparing [+Mask +Body -Brows] and [+Mask -Body +Brows]:

t.test(ad[which(ad$Interaction == "+Mask +Body -Brows"),]$Intensified,
      ad[which(ad$Interaction == "+Mask -Body +Brows"),]$Intensified)

Welch Two Sample t-test

data:  ad[which(ad$Interaction == "+Mask +Body -Brows"),]$Intensified and 
ad[which(ad$Interaction == "+Mask -Body +Brows"),]$Intensified
t = -1.9828, df = 190.78, p-value = 0.09883
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -0.1918094726 -0.0004982197
sample estimates:
   mean of x  mean of y
0.09615385 0.18230769

For masked stimuli, trading off between only the body and only the brows does not result in a significant difference in the proportion of "Intensified" responses.

Now we will compare masked stimuli that engages either only the body or only the brows, with masked stimuli that engages both the body and the brows.

Creating a new column to group [+Mask +Body -Brows] and [+Mask -Body +Brows], and separate [+Mask +Body +Brows].

ad$Comp1 <- ifelse(ad$Interaction %in% c("+Mask +Body -Brows", "+Mask -Body +Brows"),
"BodyOrBrows", "NA")
ad$Comp1[ad$Interaction=="+Mask +Body +Brows"] <- "BodyAndBrows"

T-test comparing the proportion of "Intensified" responses of masked stimuli with either only the body or only the brows, vs. stimuli with both the body and brows:

t.test(ad[which(ad$Comp1 == "BodyOrBrows"),]$Intensified,
      ad[which(ad$Comp1 == "BodyAndBrows"),]$Intensified)

Welch Two Sample t-test

data:  ad[which(ad$Comp1 == "BodyOrBrows"),]$Intensified and 
ad[which(ad$Comp1 == "BodyAndBrows"),]$Intensified
t = -3.6172, df = 163.74, p-value = 0.0003963
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -0.29232917 -0.08587596
sample estimates:
   mean of x  mean of y
0.1442308 0.3333333

Masked with one or the other engaged have a significantly smaller proportion of "Intensified" responses than masked stimuli with both engaged.

Now we will run the same tests for the unmasked conditions:

t.test(ad[which(ad$Interaction == "-Mask +Body -Brows"),]$Intensified,
      ad[which(ad$Interaction == "-Mask -Body +Brows"),]$Intensified)

Welch Two Sample t-test

data:  ad[which(ad$Interaction == "-Mask +Body -Brows"),]$Intensified and 
ad[which(ad$Interaction == "-Mask -Body +Brows"),]$Intensified
t = 0.30411, df = 207.92, p-value = 0.7613
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -0.1044297  0.1425249
sample estimates:
   mean of x  mean of y
0.7238095 0.7047619
# [-Mask +Body -Brows] and [-Mask -Body +Brows] do not significantly differ in their proportion of "Intensified" responses.
# Creating a new column to group together [-Mask +Body -Brows] and [-Mask -Body +Brows], and separate [-Mask +Body +Brows]:

```r
ad$Comp2 <- ifelse(ad$Interaction %in% c("-Mask +Body -Brows","-Mask -Body +Brows"),
"BodyOrBrows", "NA")
ad$Comp2[ad$Interaction=="-Mask +Body +Brows"] <- "BodyAndBrows"
```

# T-test:

```r
t.test(ad[which(ad$Comp2 == "BodyOrBrows"),]$Intensified,
ad[which(ad$Comp2 == "BodyAndBrows"),]$Intensified)
```

```
Welch Two Sample t-test
data:  ad[which(ad$Comp2 == "BodyOrBrows"), ]$Intensified and ad[which(ad$Comp2 == "BodyAndBrows"), ]$Intensified
t = -6.3351, df = 312.22, p-value = 8.27e-10
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-0.3120447 -0.1641458
sample estimates:
mean of x mean of y
0.7142857 0.9523810
```

# For both masked and unmasked stimuli, there was no significant difference in proportion of "Intensified" responses between stimuli that engaged only eyebrows and stimuli that engaged only the body.
# However, for both masked and unmasked stimuli, there was a significant difference between the proportion of responses of the group of stimuli that engaged one or the other (only brows or only the body), and stimuli that engaged both the brows and the body.

# Below are two figures to illustrate:

```r
ad$Comp1 <- factor(ad$Comp1, ordered=FALSE)
ad$Comp1 <- relevel(ad$Comp1, ref = "BodyOrBrows")
ad$Comp2 <- factor(ad$Comp2, ordered=FALSE)
ad$Comp2 <- relevel(ad$Comp2, ref = "BodyOrBrows")
```

# Masked stimuli:

```r
ggplot(ad[ad$Comp1 == "BodyAndBrows" | ad$Comp1 == "BodyOrBrows",]) +
aes((x = Comp1), fill = factor(Intensified)) + geom_bar(position = "fill") +
  xlab("Factors engaged") + ylab("Proportion of responses") +
  theme_bw()+
  scale_x_discrete(labels=c("Only body or only eyebrows", "Both body and eyebrows"))+
  scale_fill_manual(name = "Interpretation", labels=c("Neutral", "Intensified"),
values=c("purple4", "plum3"))
```

# Unmasked stimuli

```r
ggplot(ad[ad$Comp2 == "BodyAndBrows" | ad$Comp2 == "BodyOrBrows",]) +
aes((x = Comp2), fill = factor(Intensified)) + geom_bar(position = "fill") +
  xlab("Factors engaged") + ylab("Proportion of responses") +
  theme_bw()+
  scale_x_discrete(labels=c("Only body or only eyebrows", "Both body and eyebrows"))+
  scale_fill_manual(name = "Interpretation", labels=c("Neutral", "Intensified"),
values=c("purple4", "plum3"))
```

#### Mixed effects model:
# We will now generate a mixed effects model to test which factors are significant predictors of whether participants chose the "Intensified" option when presented with stimuli.

# Adding non-numeric columns for eyebrows and body. We won't need "mouth morpheme" as an effect in our model, because the presence or absence of a mouth morpheme is entailed by the presence or absence of a mask:

```r
ad["Body_Cond"] <- "Body"
ad$Body_Cond[ad$Body == 0] <- "NoBody"
ad["Brow_Cond"] <- "Brow"
```
```r
ad$Brow_Cond[ad$Eyebrows == 0] <- "NoBrows"

# Releveling body and brow conditions to be "No":
ad$Body_Cond <- factor(ad$Body_Cond, ordered=FALSE)
ad$Body_Cond <- relevel(ad$Body_Cond, ref = "NoBody")
ad$Brow_Cond <- factor(ad$Brow_Cond, ordered=FALSE)
ad$Brow_Cond <- relevel(ad$Brow_Cond, ref = "NoBrows")

# For the first model, we will test Mask only, as a fixed effect and use Participant as a random effect:
y1 = (glmer(ad$Intensified~Mask_Condition+(1|ParticipantID), data = ad, family = binomial))
summary(y1)
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
Family: binomial  ( logit )
Formula: ad$Intensified ~ Mask_Condition + (1 | ParticipantID)
Data: ad
AIC BIC logLik deviance df.resid
817.7 831.5 -405.8 811.7 730
Scaled residuals:
    Min      1Q  Median      3Q     Max
-1.7822 -0.5300  0.5611  0.6083  2.1807
Random effects:
   Groups   Name        Variance Std.Dev.
   ParticipantID (Intercept) 0.03266  0.1807
Fixed effects:          Estimate Std. Error   z value Pr(>|z|)
(Intercept)            -1.3249     0.1526   -8.681   <2e-16 ***
Mask_ConditionNo mask   2.3332     0.1792  13.023   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Correlation of Fixed Effects:
   (Intr)
Mask_CndtnNm -0.708

# The mask condition is a statistically significant fixed effect.
# We will try to add MMUsed as a random effect to capture the idiosyncratic variability of different mouth morphemes tested.
y2 = (glmer(ad$Intensified~Mask_Condition+(1|ParticipantID)+(1|MMUsed), data = ad, family = binomial))
summary(y2)
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
Family: binomial  ( logit )
Formula: ad$Intensified ~ Mask_Condition + (1 | ParticipantID) + (1 | MMUsed)
Data: ad
AIC  BIC   logLik deviance df.resid
818.9 837.3   -405.5   810.9      729
Scaled residuals:
    Min      1Q  Median      3Q     Max
-2.0302 -0.5221  0.4682  0.6154  2.3914
Random effects:
   Groups   Name        Variance Std.Dev.
   ParticipantID (Intercept) 0.03745  0.1935
   MMUsed (Intercept) 0.05041  0.2245
Number of obs: 733, groups: ParticipantID, 9; MMUsed, 6
```

110
Fixed effects:
  Estimate Std. Error z value Pr(>|z|)
(Intercept) -1.3221     0.1821  -7.259  3.9e-13 ***
Mask_ConditionNo mask  2.3541     0.1817  12.954  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
  (Intr) Ms_CNm
  Msk_CndtnNm -0.589

# Comparing model y1 and y2:
anova(y1,y2)

Data: ad
Models:
  y1: ad$Intensified ~ Mask_Condition + (1 | ParticipantID)
  y2: ad$Intensified ~ Mask_Condition + (1 | ParticipantID) + (1 | MMUsed)

AIC      BIC   logLik deviance df.resid
y1    3 817.67 831.46 -405.83   811.67
y2    4 818.92 837.31 -405.46   810.92 0.7504  1     0.3864

> # Adding MMUsed as a random effect did not improve the model, so we won't use it as a random effect.

> # Now, we will try adding Body_Cond as a fixed effect:

y3 = (glmer(ad$Intensified ~ Mask_Condition + Body_Cond + (1|ParticipantID), data = ad, family = binomial))

summary(y3)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
Family: binomial ( logit )
Formula: ad$Intensified ~ Mask_Condition + Body_Cond + (1 | ParticipantID)
Data: ad

AIC      BIC   logLik deviance df.resid
799.4    817.8   -395.7    791.4      729

Scaled residuals:
  Min      1Q  Median      3Q     Max
-2.2467 -0.5816  0.4451  0.6720  2.9552

Random effects:
  Groups   Name        Variance Std.Dev.
  ParticipantID (Intercept) 0.03578  0.1892
Number of obs: 733, groups:  ParticipantID, 9

Fixed effects:
  Estimate Std. Error z value Pr(>|z|)
(Intercept) -1.9175     0.2123  -9.031  < 2e-16 ***
Mask_ConditionNo mask  2.5543     0.1942  13.153  < 2e-16 ***
Body_CondBody       0.8238     0.1884   4.373  1.22e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
  (Intr) Ms-CN
  Msk_CndtnNm -0.723
  Body_CndBdy -0.683  0.357

> # Comparing y1 and y3:

anova(y1,y3)

Data: ad
Models:
y1: ad$Intensified ~ Mask_Condition + (1 | ParticipantID)
y3: ad$Intensified ~ Mask_Condition + Body_Cond + (1 | ParticipantID)

npar AIC BIC logLik deviance Chisq Df Pr(Chisq)
y1 3 817.67 831.46 -405.83 811.67
y3 4 799.44 817.83 -395.72 791.44 20.229 1 6.87e-06 ***
---
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

# y3 is significantly better.
# Now we'll try adding Brow_Cond as a fixed factor:

y4 = (glmer(ad$Intensified ~ Mask_Condition + Body_Cond + Brow_Cond + (1 | ParticipantID), data = ad, family = binomial))

summary(y4)

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) ['glmerMod']
Family: binomial (logit)
Formula: ad$Intensified ~ Mask_Condition + Body_Cond + Brow_Cond + (1 | ParticipantID)
Data: ad

AIC     BIC  logLik deviance df.resid
754.6 777.6   -372.3    744.6      728

Scaled residuals:
 Min   1Q Median   3Q   Max
-3.5550 -0.6304  0.2813  0.5571  3.0496

Random effects:
 Groups     Name        Variance Std.Dev.
ParticipantID (Intercept) 0.04538  0.213
Number of obs: 733, groups: ParticipantID, 9

Fixed effects:
 Estimate Std. Error z value Pr(>|z|)
(Intercept)            -2.9910     0.2791 -10.715  < 2e-16 ***
Mask_ConditionNo mask   2.9771     0.2186  13.621  < 2e-16 ***
Body_CondBody           1.0541     0.1955   5.390 7.03e-08 ***
Brow_CondBrow           1.3071     0.2019   6.475 9.46e-11 ***
---
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
 (Intr) Ms-CNm Bdy_CB
Msk_CndtnNm -0.760
Body_CndBdy -0.612  0.365
Brow_CndBrw -0.651  0.432  0.197

# Comparing y3 and y4:

anova(y3,y4)

Data: ad
Models:
 y3: ad$Intensified ~ Mask_Condition + Body_Cond + (1 | ParticipantID)
y4: ad$Intensified ~ Mask_Condition + Body_Cond + Brow_Cond + (1 | ParticipantID)

npar AIC BIC logLik deviance Chisq Df Pr(Chisq)
y3 4 799.44 817.83 -395.72 791.44
y4 5 754.64 777.63 -372.32 744.64 46.8 1 7.86e-12 ***
---
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

# y4 is significantly better.
# Lastly, we will try an interaction term between the body and brows:
y6 = (glmer(ad$Intensified ~ Mask_Condition + Body_Cond*Brow_Cond + (1 | ParticipantID), data = ad, family = binomial))

# Comparing y4 to y6:
anova(y4,y6)

Data: ad
Models:
  y4: ad$Intensified ~ Mask_Condition + Body_Cond + Brow_Cond + (1 | ParticipantID)
  y6: ad$Intensified ~ Mask_Condition + Body_Cond * Brow_Cond + (1 | ParticipantID)

npar  AIC  BIC logLik deviance  Chisq  Df  Pr(>Chisq)
y4  5 754.64 777.63   -372.32    744.64
y6  6 754.84 782.43   -371.42    742.84 1.7952  1  0.1803

# This does not improve the model. We will use y4 as our model.
# The intercept coefficient represents the log odds of an "Intensified" response when the
# reference levels are met (no mouth morpheme, no body, no brows).
exp(-2.991) = 0.05023717

# When the reference levels are met, the odds of getting an "Intensified" response are only
# 0.05023717 to 1.
exp(2.977) = 19.62884

# It is 19.62884 times more likely to get an "Intensified" response when changing the mask
# condition from "mask" to "no mask" (and thus introducing a mouth morpheme), with respect to
# the reference level conditions.
exp(1.054) = 2.869105

# It is 2.869105 times more likely to get an "Intensified" response when changing the Body
# condition from "No body" to "Body", with respect to the reference level conditions.
exp(1.307) = 3.695072

# It is 3.695072 times more likely to get an "Intensified" response when changing the Brow
# condition from "No brow" to "brow", with respect to the reference level conditions.

plot_model(y4, type="re")
References


