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Spatial Resolution of Quantitative Electroencephalography and Functional Magnetic Resonance Imaging During Phoneme Discrimination Tasks: An Abbreviated Meta-Analysis

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Spatial Resolution of Quantitative Electroencephalography and Functional Magnetic Resonance Imaging During Phoneme Discrimination Tasks:

An Abbreviated Meta-Analysis

Emily Jean Jacobs

A thesis submitted to the faculty of
Brigham Young University
in partial fulfillment of the requirements for the degree of

Master of Science

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ABSTRACT

Spatial Resolution of Quantitative Electroencephalography and Functional Magnetic Resonance Imaging During Phoneme Discrimination Tasks: An Abbreviated Meta-Analysis

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Master of Science

Phonological processing, the ability to recognize and manipulate the sounds of one's native language, is an essential linguistic skill. Deficits in this skill may lead to decreased social, educational, and financial success (Kraus & White-Schwoch, 2019). Additionally, phonological disorders have been shown to be highly variable and individualized (Bellon-Harn & Cradeur-Pampolina, 2016) and therefore difficult to treat effectively. A better understanding of the neural underpinnings of phonological processing, including the underlying skill of phonemic discrimination, could lead to the development of more individualized and effective intervention. Several studies, some using quantitative electroencephalography (qEEG) and others using functional magnetic resonance imaging (fMRI), have been conducted to investigate these neural underpinnings. When considering the relative strengths and weaknesses of qEEG and fMRI, the scientific community has traditionally believed qEEG to be excellent at determining when brain activity occurs (temporal resolution), but to have limited abilities in determining where it occurs (spatial resolution). On the other hand, the reverse is believed to be true for fMRI. However, the spatial resolution of qEEG has improved over recent decades and some studies have reached levels of specificity comparable to fMRI. This thesis provides an abbreviated meta-analysis determining the accuracy and consistency of source references, or areas where brain activation is determined to originate from, in qEEG studies evaluating phonemic discrimination. Nineteen experiments were analyzed using the Comprehensive Meta-Analysis software. A study's event rate was defined as the number of times an anatomical area was coded as a source reference, divided by the participants in the study. Results show that each of these experiments had relatively low event rates, culminating into a summary event rate of 0.240. This indicates that qEEG does not provide source references that are as accurate or consistent as fMRI. This meta-analysis concludes that although there is research suggesting qEEG may have developed to be comparable to fMRI in spatial resolution, this is not supported in the analysis of qEEG studies focused on phonemic discrimination.

Keywords: spatial resolution, electroencephalography, functional magnetic resonance imaging, phoneme discrimination task

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Lastly, I would like to thank my family, particularly my parents for encouraging me to pursue my dreams through further schooling and helping to support and shelter me through graduate school. Most of all, I want to thank my husband, Chris, for helping me through the stress, tears, and confusion I confronted through this process. His support got me through this project and I could not have done it without him.

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DESCRIPTION OF THESIS STRUCTURE AND CONTENT

This thesis, *Spatial Resolution of Quantitative Electroencephalography and Functional Magnetic Resonance Imaging During Phoneme Discrimination Tasks: An Abbreviated Meta-Analysis*, is written in a hybrid format that combines traditional thesis requirements with journal publication formats. The preliminary pages of the thesis reflect requirements for submission to the university. The thesis report is presented as a journal article and conforms to length and style requirements for submitting research reports to professional journals in speech and language.

This thesis format contains two reference lists. The first reference list contains references included in the journal-ready article and the second list is the annotated bibliography, found in Appendix A. Additionally, the original coding sheet used while gathering the articles included in this meta-analysis was divided into four tables, which can be found in Appendix B.

Background

Phonemic Discrimination and Categorization

One of the first skills that needs to be acquired for language development is phonological processing, or the ability to recognize and manipulate the sounds of one's native language. Essential to this ability are the underlying skills of phonemic discrimination and categorization; the ability to determine when two speech sounds are different and the ability to put groups of allophones into the same category, respectively. These skills are necessary for both receptive and expressive language and are additionally essential to literacy. Studies have shown that children who struggle with phonological skills are likely to exhibit internalizing behaviors, such as withdrawal and feelings of anxiety, depression, and low self-esteem, as well as externalizing behaviors like aggression and delinquency (Daal et al., 2007). It is not surprising to find, that, as with other language skills, phonological deficits can lead to decreased social, educational, and financial success (Kraus & White-Schwoch, 2019).

Unfortunately, these underlying language skills of phonemic discrimination and categorization are diminished in some individuals, such as those who have language impairment, reading impairment, or various neurodegenerative diseases. While there are therapy techniques that exist to help treat these disorders, such as modeling and expansion, cloze procedures, and contrastive word pairs, phonological disorders have proven to be highly variable and individualized (Bellon-Harn & Cradeur-Pampolina, 2016), making them difficult to treat. If there was more information regarding the neural underpinnings of phonological processing and the related skills of phonemic discrimination and categorization then more individualized and effective intervention may be possible for those with phonological disorders.

Researchers have conducted many studies using various neuroimaging techniques attempting to understand the processes of phonemic categorization and discrimination and the areas of the brain where they occur. This thesis will focus on quantitative electroencephalography (qEEG) and functional magnetic resonance imaging (fMRI): techniques commonly used to study these processes.

Electroencephalography

Electroencephalography (EEG) is a neuroimaging technique that has been used since the 1960's. This technique uses electrodes, placed uniformly across the scalp, to measure and record electrical impulses produced by brain activity. These impulses are generated by columns of neurons in the superficial layers of gray matter in the brain (McPherson et al., 2020). As internal cognition or external stimuli occur, positive and negative electrical charges are generated in the neurons located in areas corresponding to the stimuli. As one neuron has an electrical reaction, the electrical charges of the neurons surrounding it are also affected, which, in turn, influence the charges of the neurons around them. Because of this ripple effect, electrical impulses that occur deep within the brain can be recorded and amplified from scalp electrodes that enhance electrical brain activity (Jackson & Bolger, 2014; McPherson et al., 2020).

One of the primary ways that EEG information may be analyzed is through event-related potentials (ERPs). These are time locked changes in the EEG signal resulting from motor, sensory, or cognitive stimuli or events. It is theorized that after such an event, many neurons that are oriented similarly and are in close proximity to one another form a neural network and have similar reactions. Their synchronous electrical responses are summed by EEG, resulting in an ERP (Sur & Sinha, 2009).

Some of the ERPs most commonly used to study phonemic discrimination are the mismatch negativity (MMN), P200, and N100. The MMN represents a change in brain activity when a participant identifies a difference between two successive sensory stimuli and occurs approximately 200 ms post-stimulus onset (Kraus et al., 1992). The N100, or N1 wave, represents the electrical activity that occurs as the brain matches a new, unexpected, stimulus with stimuli previously experienced. The N100 wave peaks between 90 and 200 ms post-stimulus presentation (Sur & Sinha, 2009). The P200, or P2, wave, is particularly valued in auditory EEG research because its amplitude and latency change according to stimuli characteristics, such as pitch, duration, and intensity (Remijn et al., 2014). The P200 wave typically peaks between 100 and 250 ms post-stimulus onset (Sur & Sinha, 2009).

Researchers using ERP data, and consequently EEG, are able to do so knowing that the data has remarkably high temporal resolution, down to the millisecond. Unfortunately, EEG has traditionally been known to have relatively poor spatial resolution, usually a few centimeters (Milner et al., 2014). This reduced spatial resolution is the result of the ripples of electrical current expanding as they spread from one neuron to the next. Additional distortion occurs as the signal travels through different anatomical structures with varying densities, such as white matter, meninges, skull, and skin (Jackson & Bolger, 2014). By the time the signal reaches the scalp electrodes, it has expanded and been distorted to the point that there are infinite possibilities for the source of the signal; this is known as the inverse problem (Strauss, 2015). Increasing the electrode density can help improve spatial resolution; some EEG studies have used as many as 256 electrode channels to obtain more precise localization, but the results are limited (Milner et al., 2014).

Quantitative Electroencephalography

Quantitative EEG (qEEG) was developed to improve the spatial resolution of EEG. This method of EEG takes the two-dimensional spatial information provided by EEG, runs it through a statistical system, and then reconstructs the brain activity in a three-dimensional array (McPherson et al., 2020). Through the years, many different systems and algorithms have been developed for qEEG. Initially, attempts to determine source localization were made based on models in which the head was shown to be spherical and the whole source space was homogenous in its density and conductivity characteristics (Michel & He, 2019). Obviously, this led to source localization that had very poor accuracy.

As qEEG techniques continued to develop, however, accuracy improved drastically. One of the factors that has led to increased accuracy was the development of more realistic head models. EEG researchers developed several different types of head models. One method, the boundary element method (BEM) uses three layers, representing the brain, skull, and scalp. Within each layer, electrical homogeneity is assumed, but each layer is given different conductivity characteristics (Michel & He, 2019).

Another type of head model, the finite element method (FEM) considers the heterogeneity in the conductivity of white matter and uses MRI anatomical information to accurately distinguish and segment various brain tissues (Michel & He, 2019).

Another method, spherical head model with anatomic constraints (SMAC), and the local adjustment of that method (LSMAC), uses the simplicity of a spherical model, but takes into account a person's individual anatomy. This approach considers the head geography and adjusts the MRI brain into the "best-fitting sphere," which then allows analysis to be done for this individualized multi-shell spherical model (Michel & He, 2019).

When MRI images are available, it is now common to use an individual's MRI as a head model. This allows consideration for the head shape, the effects of varying bone density in different areas of the skull, and the density and conductivity characteristics of brain matter, cerebrospinal fluid, skull, and scalp (Michel & He, 2019). These adjustments have allowed qEEG to localize the source of ERPs with 70 to 84% accuracy (Brodbeck et al., 2011; Michel & He, 2019)). Some qEEG systems are able to reach spatial resolution of five to 10 mm (Bidelman & Walker, 2019).

Functional Magnetic Resonance Imaging

Magnetic resonance imaging (MRI) is a neuroimaging technique that can produce two- and three-dimensional images with very high spatial resolution by using a strong magnetic field to place the hydrogen atoms in the body slightly out of alignment and subsequently measuring how long it takes them to return to alignment (McPherson et al., 2020). In this way, different types of tissue can be accurately differentiated. Functional MRI (fMRI) is a subset of MRI that can look at the brain's reaction to external stimuli or the areas of the brain influenced by internal cognition. This is done by measuring the blood-oxygen-level-dependent (BOLD) signal, or hemodynamic response (McPherson et al., 2020). When a brain area is activated because of external stimuli or internal cognition, blood flow is required to that area. The fMRI machine can track this blood flow and thus determine the areas where activation is occurring with voxels as small as one mm^2 (McPherson et al., 2020).

Unfortunately, this high spatial resolution comes with a trade-off. While EEG can record electrical activation almost instantaneously, it takes several seconds for blood to arrive in activated brain areas. While the blood is traveling, multiple other areas of the brain often become active, which then also require blood. This is reflected in the fMRI and results in low temporal resolution (Milner et al., 2014).

Pragmatic Considerations

Both EEG and fMRI are highly valued and useful tools in neuroimaging that have contributed greatly to the understanding of many brain functions, including phonemic discrimination and categorization. Ideally, a study aiming to determine the neural underpinnings of a brain process can use both EEG and fMRI to take advantage of the relative strengths of each. However, for several reasons, this is often not practical if a researcher is seeking to produce a study with a large and diverse sample without an enormous budget.

A study using MRI is often limited in the number of participants it can involve for several reasons. One of them is the safety precautions involved in conducting an MRI. While the MRI environment is typically safe for the average person, there are risks involved. Complications can arise due to the strong magnetic field the machine creates. This field can attract magnetic items to it at a high velocity, as well as affect implants within the patient and cause unwanted movement, malfunction of the device and/or MRI machine, and potential burns on the participant. This potential for the shifting of metal in the body excludes those who have metal implants, such as cochlear implants or pacemakers, from being included in MRI studies. Additionally, movement during the scan can invalidate the MRI data (Brodbeck et al., 2011), making it hard to include people who have difficulty laying still for a long time, such as children. Additionally, the loud and rather confined environment makes long scans difficult and uncomfortable for participants (U.S. Food and Drug Administration [FDA], 2017). The FDA (2017) reports that out of millions of MRIs given every year in the USA, they receive approximately 300 reports of adverse events occurring.

The MRI environment can also influence the data received during combined EEG-fMRI studies. The MRI machine has been known to cause artefacts in the EEG data. The loud auditory environment is particularly problematic in combined studies using auditory evoked potentials because it makes effectively delivering stimuli difficult. Additionally, the sound of the scanner can also produce a BOLD signal, unrelated to the stimuli, in auditory processing areas. The constant noise has also been shown to reduce the auditory brain activity due to masking and habituation (Mayhew et al., 2010).

Another important consideration is the cost of MRI. In the United States, the cost depends on the facility in which an individual is getting an MRI and the state they are in, but prices can vary from around $444 to $1,468 for a limb MRI (Pflanzer, 2017). MRIs conducted at universities for research purposes can be $555-600 per hour (University of Michigan Functional MRI Laboratory, 2020; Yale School of Medicine, 2019).

On the other hand, EEG studies are relatively low-cost, safe, and available for a wide population. The cost of a one-hour EEG session on average is estimated to be $84.69 (Abend et al., 2015). There are few risks involved in the procedure, the most extreme of which is the potential for a slight scratch from the blunted needle that injects gel into the electrode wells. The procedure is also relatively flexible in that the patient can be sitting or lying down and the set-up can be portable. Finally, while head and eye movements can cause some artefacts, small movements of the patient will not invalidate the data (Johns Hopkins Medicine*,* 2020).

Some participant characteristics need to be taken into consideration when doing EEG research. For example, researchers often exclude left-handed and ambidextrous individuals from studies because these populations are more likely to show atypical hemispheric specialization. Researchers also need to keep in mind that there are known and predictable differences between the ERPs of men and women as well as across the lifespan (Remijn et al., 2014). However, there are otherwise no characteristics that would exclude someone from getting an EEG. This allows for a large pool of potential participants as well as the possibility for studies on populations that might be more difficult to obtain fMRI data from.

Need for a Meta-Analysis

Considering the price, safety, and availability differences between qEEG and fMRI, it seems a systematic evaluation of the spatial ability of qEEG would be welcome in the scientific community, if only to confirm that fMRI still presents the most accurate representations of the brain. Thus, the researcher conducted a meta-analysis; a statistical procedure used to combine the results of multiple studies (Cooper & Cooper, 2010), to compare qEEG spatial information to fMRI and to determine the level of agreement of spatial findings in qEEG studies using phonemes.

Statement of the Purpose

This meta-analysis initially sought to answer the question, “What differences are seen in spatial distribution of brain activation resulting from phoneme discrimination when measured by qEEG compared to fMRI in healthy young adults?” The advent of the Covid-19 pandemic and restriction of the EEG and MRI laboratories at Brigham Young University for research resulted in a modification of the study question: That is, are there consistencies between what is expected in source identification using qEEG and known fMRI source identification in the literature?

Quantitative EEG has come a long way since the 1960’s, and there is some evidence to suggest that it can produce spatial information on source generators of ERPs on a level similar to fMRI. A 2011 study by Brodbeck et al. found that high-resolution EEG recordings, when coupled with an individual’s MRI, can localize epileptic activity with 84% accuracy, compared to 76% accuracy seen in MRI-alone. Additionally, multiple qEEG studies, using either individual or template MRI head models, have identified cortical generators to Brodmann area-levels of specificity (Jantzen et al., 2014; Strauss, 2015; Turner, 2018) or greater (Liebenthal et al., 2013; Mayhew et al., 2010); a level comparable to some fMRI studies (Mayhew et al., 2010; Milner et al., 2014). It should be noted that these studies were not using sensory stimuli but were looking at epileptic sources. If this meta-analysis indicates that qEEG can provide spatial information at a level of specificity similar to fMRI, this could allow for more research to be conducted using qEEG, thereby having less of a reliance on expensive and exclusive neuroimaging techniques.

In order to conduct a valid meta-analysis, the included articles need to have similar goals and study similar topics (Impellizzeri & Bizzini, 2012). Because of this constraint for homogeneity, as well as the need for more information regarding understanding of phonemic discrimination, the studies included in this meta-analysis will look specifically at phonemic discrimination tasks.

Method

Identification and Selection of Source Studies

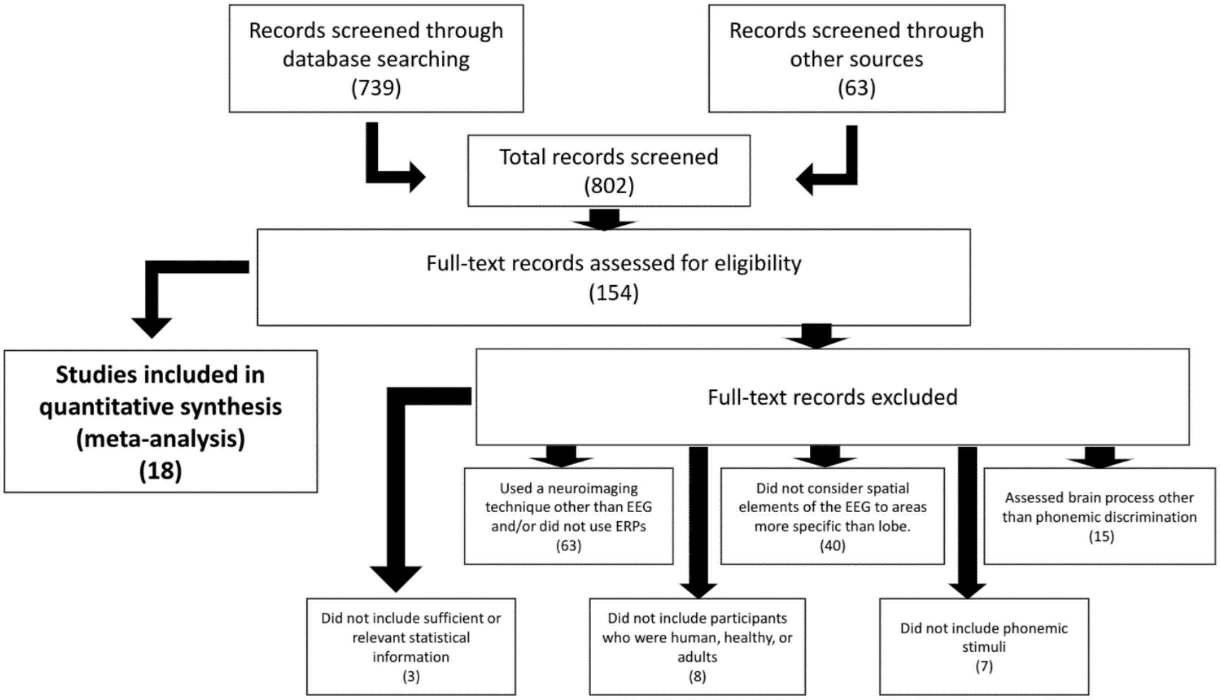
The search for studies that would provide data for the spatial specificity of qEEG when measuring phonemic discrimination began on the internet. The databases PubMed Central, MEDLINE (PUBMED), Web of Science, CINAHL, Embase, and Google Scholar were used to find articles that fit the inclusion criteria. The search terms “spatial distribution of brain activ*”, “quantitative electroencephalography”, qEEG, EEG, electroencephalogram, event related potential, ERP, evoked potential, MMN, P300, cortical generator, phoneme discrimination, phonemic discrimination, phoneme categorization, phonemic categorization, speech-sound discrimination, sound discrimination, phonem* awareness, phonological awareness, and auditory discrimination were used in appropriate combinations. Additionally, the researcher conducted a manual search of the references of articles that seemed particularly relevant.

To reduce publication bias, limits were not placed on the year of publication, language, or peer-review status. However, some search restrictions were used to exclude irrelevant studies. In MEDLINE and CINAHL, filters were placed on the searches to limit them to experiments with human participants aged 19 to 44. In some searches, terms were included to exclude studies in which the subjects were animals, children, or adults with neurological or hearing disorders, injuries, or conditions (e.g., schizophrenia, dyslexia, aphasia, autism, tinnitus, etc.).

As shown in Figure 1, the internet search resulted in 739 hits. The researcher then reviewed the titles and abstracts of these hits and noted the titles that seemed relevant. Combined

Figure 1

Flow Chart Showing Identification and Selection Process of 18 Articles (19 Experiments).



with the title search within reference sections of related articles, this resulted in 154 noted articles. The researcher read and assessed the remaining articles for eligibility based on the inclusion criteria. One of the included articles, Maiste et al. 1995, conducted four different experiments, two of which fit the inclusion criteria. Consequently, 18 studies, representing 19 experiments, were included in this meta-analysis.

Inclusion Criteria

Articles were selected based on six inclusion criteria developed to ensure that studies would be similar enough to be comparable and include enough statistical information to be analyzed. Because this meta-analysis is meant to determine the level of spatial resolution of qEEG, included articles needed to be experimental studies that utilized qEEG and ERPs. Use of a different neuroimaging technique in conjunction with qEEG did not automatically disqualify an article, but the qEEG data needed to be presented separately from the other neuroimaging data.

Because this study aimed to provide more information on phonemic discrimination, each study had to include a phonemic discrimination task to fit the second inclusion criterion. Studying phonemic discrimination was additionally important because it provided a specific process to compare the spatial distributions seen during qEEG and fMRI. Similarly, the third inclusion criterion required the study to include phonemic stimuli. Fourth, studies needed to consider areas of brain involvement with specificity to the level of lobe or greater in order to provide studies remotely comparable to fMRI.

The fifth inclusion criterion was that the study participants needed to be neuro-typical human adults with normal hearing. This meta-analysis is seeking to provide information on phonemic processing in the typical brain. Additionally, this was meant to help provide some level of homogeneity to the included studies.

Finally, every study needed to include enough statistical information about their results that the Comprehensive Meta-Analysis (CMA) software could process it effectively. Appendix B includes four tables that list the basic information of the 19 experiments included in the meta-analysis.

Data Abstraction

The researcher coded all of the articles that met the inclusion criteria. First, the researcher coded for basic study characteristics including sample size, number of males and females included, age range, handedness, hearing, and overall health status of participants. Any phonemic stimuli used, experimental paradigm, number of electrodes, ERPs analyzed, and any regions of interest (ROIs) and/or brain areas discussed in each study were also coded.

Next, the researcher searched the results section of each article to record statistical information reported regarding the ERP amplitude responses to the various experimental conditions tested. This included the sample size (n), mean, standard deviation, and distribution lower and upper limits. Additionally, the researcher coded any t tests, along with the t values and the p value of the t values. Any F tests and the p value of the F tests were also coded. Finally, the ROIs and other brain areas where activation occurred in the studies were coded into more general areas; this adjustment can be seen in the tenth column of Table A3 in Appendix B.

Data Analysis

Following coding, this statistical information was entered into the CMA software. This software computed the event rate, upper and lower limits, logit event rate, standard error, p value, and z value of the results of all the studies.

Statistical Analysis

After these statistical values were calculated, CMA formulated the data into a variety of representations to show the results. Tables were produced to concisely report the data, which included the sample size, number of events, event rate, logit event rate, standard error, lower and upper limits, variance, *z* value, *p* value, and Cochran's *Q* value. A forest plot and funnel plot were used to provide graphical representations of the results. A forest plot was used because it is an effective way to illustrate the heterogeneity between studies by visualizing the different sample sizes, and therefore weight, of each study. Additionally, the forest plot gives a visual representation of the pooled results of all the studies while simultaneously providing information on the confidence intervals and precision of each study. Funnel plots also effectively show the results and study precision of each included study. More importantly, though, a funnel plot was used because the symmetry of a funnel plot can help illustrate publication bias in the meta-analysis. This study is an abbreviated meta-analysis due to the fact that not all possible meta-analytical analyses were utilized to describe the results.

Results

The purpose of this study was to determine the consistency of source identification in qEEG compared to the known fMRI source identification. To accomplish this, the researcher found 19 experiments that fit six inclusion criteria: each experiment was conducted using qEEG and ERPs, studied phonemic discrimination tasks, used phonemic stimuli, mentioned areas of electrical activity with at least lobe-level specificity, studied neuro-typical healthy adults, and provided sufficient statistical information on any spatial findings to run through a statistical program like CMA. The spatial results of each of these experiments were then analyzed through

CMA to reveal how accurate each qEEG study was in estimating where they saw electrical activity.

Fixed-Effect Versus Random-Effects Model

The decision to use a fixed- or random-effects model was not a clear one. In many ways, it seemed that a random-effects model would be most appropriate. In the 2009 book *Introduction to Meta-Analysis*, Borenstein et al. note that a random-effects model is appropriate when a researcher has studies that were conducted independent of each other and the studies are not functionally equivalent. They continue that these studies likely vary in ways that would impact the results and would make it unwise to assume a common effect-size (pp. 83-84). The studies collected for this meta-analysis are indeed functionally different and there was no reason to assume a common effect size.

However, Borenstein et al. (2009) acknowledge that the random-effects model cannot be applied correctly when there is a small number of studies in the analysis because the estimate of between-study variance will have poor precision (p. 84). Nineteen experiments is a small sample size for a meta-analysis, and it was consequently determined that a fixed-effect model should be used to analyze the data. A fixed-effect model will show descriptive analysis of the included studies, but it will prevent the results from being applicable to a wider population (Borenstein et al., 2009).

Study Characteristics

The experiments in this meta-analysis included 16 articles published in peer-reviewed journals and three that were unpublished theses or dissertations. The combined sample size represents 421 participants ranging in age from 17.9 to 61.45 years old. Sixteen of the experiments used an oddball paradigm, while two used a dichotic listening task and one used a forced choice task. There were 11 experiments with purely active tasks, six with purely passive, and two that included both active and passive tasks. Each study implemented qEEG but they differed in the number of electrode channels they used. Ten of the studies used 64-electrode arrays, one used 65 electrodes, three studies used 20 to 30 electrodes, and four used eight to 14 electrodes.

Individual Study Data

Table 1 shows the summary statistics of the individual studies (*n*=19). The events refer to the coding of the anatomical areas identified in each study. Sample size refers to the number of participants in the study. Event rate refers to the total events per person in the study. This number represents the weight of each study; for example, the event rate for Aerts is 0.021, indicating that this study contributed 2.1% to the summary event rate. Logit event rate is used when the variables are categorical, thus allowing a regression analysis which otherwise uses a linear assumption, which categorical data violates.

Publication Bias

Publication bias refers to the characteristics (material selected as it relates to inclusion and exclusion criteria) of the sample (i.e., publications) used in the meta-analysis. It is an evaluation of the methods used in the study and the findings of the study. Table 2 lists the statistics for publication bias that are used in the construction of Figure 2, which illustrates publication bias through a funnel plot (effect size by sample size).

Table 1

Summary of Study Statistics

Study Name	Events	Sample Size	Event Rate	Logit Event Rate	*SE*
Aerts et al., 2017	1	47	0.021	-3.829	1.011
Alain et al., 2010	2	20	0.100	-2.197	0.745
Bidelman & Lee, 2015	7	20	0.350	-0.619	0.469
Bidelman & Walker, 2017	5	10	0.500	0	0.632
Bidelman & Walker, 2019	4	20	0.200	-1.386	0.559
Bidelman et al., 2020	2	15	0.133	-1.872	0.760
Brunelliere, 2009	4	14	0.286	-0.916	0.592
Diaz et al., 2008	7	31	0.226	-1.232	0.430
Jantzen et al., 2014	3	12	0.250	-1.099	0.667
Jin et al., 2014	7	31	0.226	-1.232	0.430
Kayser & Tenke, 2006	4	66	0.061	-2.741	0.516
Kramer, 2014	5	22	0.227	-1.224	0.509
Maiste et al., 1995 (ex. 2)	8	10	0.800	1.386	0.791
Maiste et al., 1995 (ex. 4)	7	10	0.700	0.847	0.690
Plumridge et al., 2020	8	42	0.190	-1.447	0.393
Sorensen, 2018	2	18	0.111	-2.079	0.750
Strauss, 2015	6	20	0.300	-0.847	0.488
Szymanski et al., 1999	5	13	0.385	-0.470	0.570
Wagner et al., 2012	5	24	0.208	-1.335	0.503

Note. Events: 1, Frontal Lobe; 2, Temporal Lobe; 3, Superior Temporal Gyrus; 4, Temporal-Parietal-Central Lobe; 5, Post Temporal Lobe; 6, Cingulate Cortex; 7, Heschl's Gyrus; 8, Middle Parietal Lobe.

[a] Jin et al. 2014 used the MMN data from Diaz et al. 2008 to further investigate the spectral dynamics of phoneme learning.

Table 2 includes statistics determined for both the fixed- and random-effects models. Although it was ultimately decided to use the fixed-effect model, the random-effects model was provided for the purpose of comparison. The effect size describes the accuracy of spatial resolution in the 19 qEEG studies; the point estimate is an approximation of this value. The standard error (*SE*) shows the variation we can expect to see in the mean effect size if many independent samples were taken, whereas the variance indicates the average difference between the effect sizes of each individual experiment. A 95% confidence interval was calculated, the range of the effect sizes is seen in the lower limit (*LL*) and upper limit (*UL*) columns.

Table 2

Effect Size by Sample Size for Publication Bias for Both Fixed and Random Effects

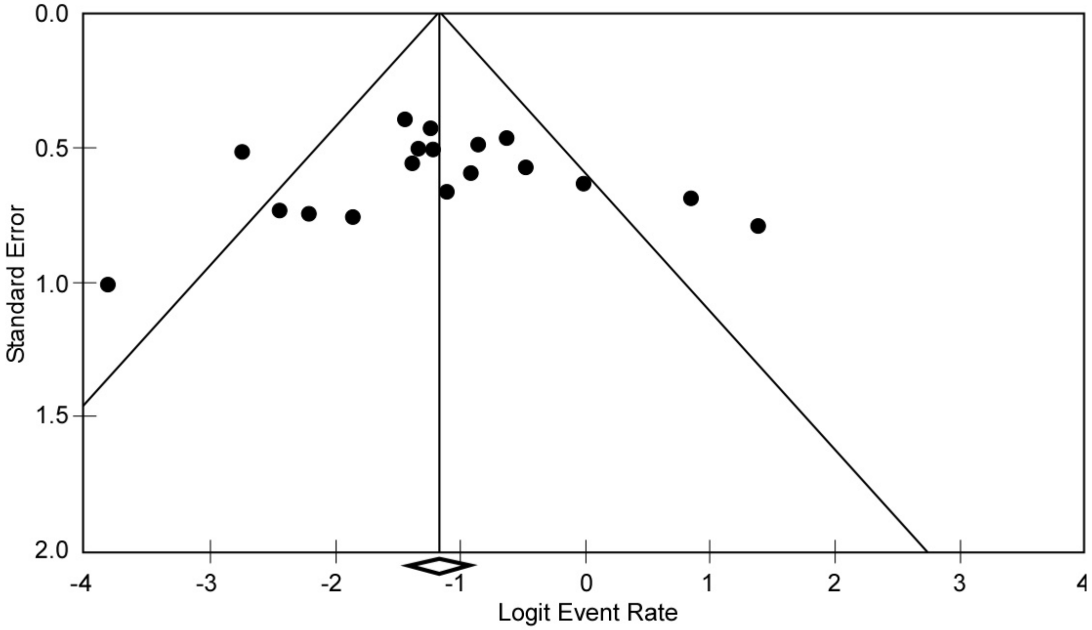
Model	Effect Size and 95% Confidence Interval						Test of Null (2-Tail)		Heterogeneity			
	Number studies	Point Estimate	*SE*	Variance	*LL*	*UL*	*z* value	*p* value	*Q* value	*df* (*Q*)	*p* value	χ^2
Fixed	19	-1.155	0.127	0.016	-1.405	-0.905	-9.056	0.000	47.151	18	0.000	63.019
Random	19	-1.142	0.212	0.045	-1.558	-0.726	-5.376	0.000				

Finally, Table 2 gives the results of two tests of heterogeneity. This included Cochran's *Q*, which determined the differences between the effects of each experiment compared to the overall effect of the studies. This *Q* value was calculated with 18 degrees of freedom (*df*) and yielded $p \leq 0.000$. A chi-squared test (χ^2) of heterogeneity was also completed; this test shows whether the differences seen in the results could have occurred simply due to chance. This test resulted in $\chi^2 = 63.019$, indicating that there a high level of heterogeneity and little consistency between studies.

Table 2 also shows the results of a two-tailed test that was conducted to determine the likelihood of the null hypothesis; that the effect sizes between the studies would be homogenous. For the fixed-effect model, this showed $z = -9.056$ and $p \leq 0.000$.

Figure 2

Funnel Plot of Publication Bias



The funnel plot seen in Figure 2 is a graphical representation of the study results (x-axis, logit event rate) and the precision (y-axis, standard error). The lines represent the 95% confidence intervals, and the vertical line represents the overall study effect. The more powerful studies are located toward the top of the figure, and the less powerful studies are located toward the bottom. The asymmetry of the graph is an indication of the heterogeneity of the data. The overall results, represented by the vertical line, indicate an overall bias towards heterogeneity.

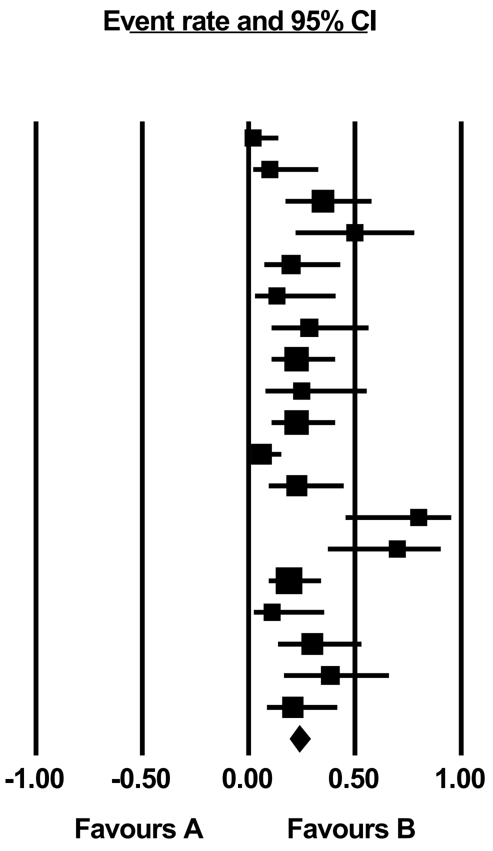
Event Rate

Figure 3 includes both a table and a forest plot. The table provides information regarding the event rate of each individual study and a summary event rate using the fixed-effect model in the bottom row. The event rates were calculated with a 95% confidence interval, the lower and upper limits are provided for each experiment, as are a *z* value and *p* value.

Figure 3

Forest Plot and Statistic for Each Study

Study name	Statistics for each study				
	Event rate	Lower limit	Upper limit	Z-Value	p-Value
Aerts, 2017	0.021	0.003	0.136	-3.788	0.000
Alain, 2010	0.100	0.025	0.324	-2.948	0.003
Bidelman, 2015	0.350	0.177	0.574	-1.320	0.187
Bidelman, 2017	0.500	0.225	0.775	0.000	1.000
Bidelman, 2019	0.200	0.077	0.428	-2.480	0.013
Bidelman, 2020	0.133	0.034	0.405	-2.464	0.014
Brunelliere, 2009	0.286	0.111	0.561	-1.549	0.121
Diaz, 2008	0.226	0.112	0.404	-2.868	0.004
Jantzen, 2014	0.250	0.083	0.552	-1.648	0.099
Jin, 2014	0.226	0.112	0.404	-2.868	0.004
Kayser, 2006	0.061	0.023	0.151	-5.313	0.000
Kramer, 2014	0.227	0.098	0.444	-2.405	0.016
Maiste, 1995 (ex. 2)	0.800	0.459	0.950	1.754	0.080
Maiste, 1995, (ex. 4)	0.700	0.376	0.900	1.228	0.220
Plumridge, 2020	0.190	0.098	0.337	-3.682	0.000
Sorensen, 2018	0.111	0.028	0.352	-2.773	0.006
Straus, 2015	0.300	0.141	0.527	-1.736	0.082
Szymanski, 1999	0.385	0.170	0.656	-0.824	0.410
Wagner, 2012	0.208	0.089	0.413	-2.656	0.008
	0.240	0.197	0.288	-9.056	0.000



Note. Favours A, the level of accuracy relative to the source expected in the qEEG; Favours B, variance from accuracy expected in the qEEG.

The right side of Figure 3 includes a forest plot that provides a visual representation of the event rates and confidence intervals of each experiment. The diamond at the bottom of the forest plot represents the summary event rate. Because this forest plot was constructed using the fixed-effect model, the results of each experiment were weighted according to the number of participants, with the larger experiments carrying more weight than the smaller ones; this is reflected in the size of the squares in the forest plot. The left side of the forest plot, labeled

Favours A, represents the level of accuracy relative to the source expected to be seen in the qEEG. The right side of the forest plot, labeled Favours B, represents the variance from that accuracy. The center vertical line, labeled 0.00, is the line of no effect: the point where there is no consistent source identification.

Discussion

This meta-analysis sought to determine the consistency between qEEG spatial resolution across studies compared to fMRI spatial resolution. The data indicates that qEEG does not provide source references that are consistent across studies.

Publication Bias

As shown in Figure 2, the larger studies are clustered towards the top and are somewhat symmetrical. There are missing studies in the middle and bottom of the plot resulting in an overall asymmetry that suggests the presence of publication bias. Specifically, because of the asymmetrical dispersion at the top of the plot and the lack of studies in the middle or bottom, the publication bias would indicate that the sample is biased towards larger studies with more homogeneity of material. This absence of moderate and smaller studies suggests that there is information missing, which may have influenced the overall effect size of the analysis.

Heterogeneity

The included qEEG experiments were all primarily focused on phonemic discrimination. However, the processes, the stimuli and paradigms used, as well as the evoked responses, varied widely between studies. Consequently, the levels of heterogeneity computed by Cochran's Q and the chi-squared tests were consistent with this suspicion of heterogeneity. Table 2 shows Q = 47.151, which is high with respect to $df = 18$. The chi-squared test showed $\chi^2 = 63.019$ and $p \leq 0$. These scores indicate substantial heterogeneity. It is important to note, however, that Cochran Q

is a low-powered statistic when applied to a small sample size, which this meta-analysis is. Even so, because the two statistics are giving the same result, it can be concluded that the effect sizes are heterogeneous. These levels of heterogeneity suggest that the variation seen between the effect sizes of the studies could be, at least in part, due to the variation in study characteristics.

Event Rate

The event rate (event ratio) is a measure of the number of times an anatomical area was identified, divided by the number of people in the study. As seen in Figure 3, only three studies showed an event rate above 0.50, and none of those experiments reached significance, indicating that their event rate may have been due to chance. The diamond at the bottom of the forest plot, in Figure 3, representing the summary event rate, does not touch the vertical lines next to it. This would suggest that there are significant differences, at the .05 level, across studies in their ability to identify neural sources consistently. The summary event rate also suggests that the actual results varied widely from the expected results. The large z value, $z = -9.056$, also supports this conclusion. Ultimately, the figure shows that source identification most likely favors fMRI, which is somewhat of a “gold standard,” as opposed to qEEG. The overall z value and subsequent p value show this bias is statistically significant. Therefore, qEEG does not provide source references that are as accurate or consistent as fMRI.

Conclusion

The results of this meta-analysis indicated that the qEEG studies included are not as accurate or consistent in source localization as fMRI studies. Because a fixed-effect model was used, the results of this study cannot be generalized to all qEEG studies. However, it does suggest that studies may have been assuming source localization that might be incorrect.

Overall, this meta-analysis made it clear that there is simply not enough information available to effectively compare qEEG spatial resolution to that of fMRI. In months of searching, the researcher located only 19 qEEG experiments that included spatial information to the level of lobe or greater. This was undoubtedly because her search was limited to experiments focused on phonemic discrimination in humans. However, research like the 2011 study by Brodbeck et al., which found that high-resolution qEEG paired with an individual's MRI could identify areas of epileptic activity with greater accuracy than MRI-alone, suggest that the technology is available for qEEG to play a larger role in research and medicine as a means of provided affordable, flexible, and inclusive neuroimaging. However, more research and meta-analyses looking into the spatial accuracy and consistency of qEEG is necessary to ensure accurate findings.

Limitations

This study is limited in its scope due, first, to its small sample size. The inclusion criteria used were necessary because this meta-analysis was specifically researching phonemic discrimination. However, the strict inclusion criteria led to only 19 experiments being included in this meta-analysis. The disparity between study characteristics made a random-effects model most appropriate. However, the random-effects model requires a large number of studies to avoid error in the estimate of between-study variance (Borenstein et al., 2009). The small number of studies may have influenced the results as it led to the use of a fixed-effects model, which additionally makes the results ungeneralizable beyond those included in the present study.

It is also possible that this meta-analysis' focus on phonemic discrimination led to the variability seen within and between studies. Phonemic discrimination is a complex linguistic process, and it is possible that it does not occur in the same brain areas in all people. Future meta-analyses researching consistency of qEEG spatial resolution may have vastly different results if the studies they include use less complex stimuli, such as simple tones.

Additionally, although the researcher did all she reasonably could to find studies that fit the inclusion criteria, it is possible that some were missed. This small sample size may have allowed for sampling bias to occur; the researcher tried to avoid this by not imposing limits on the year of publication, language of publication, or publication status.

In order to avoid bias and human error in identifying and coding articles, meta-analysis guides state that these tasks should not be done by one person (Cooper & Cooper, 2010; Impellizzeri & Bizzini, 2012). Because of the timing of this study and the Covid-19 pandemic, the researcher found and coded all of the articles herself. To try to avoid mistakes, the researcher developed and followed inclusion and exclusion criteria as well as a clear coding sheet. All coding was double-checked.

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APPENDIX A

Annotated Bibliography

Aerts, A., Strobbe, G., Mierlo, P. V., Hartsuiker, R. J., Corthals, P., Santens, P., & Letter, M. D. (2017). Spatiotemporal differentiation in auditory and motor regions during auditory phoneme discrimination. *Acta Neurologica Belgica*, *117*(2), 477–491. https://doi.org/10.1007/s13760-017-0761-3

Objective: This study aimed to examine the influence place, manner, and voicing has on phoneme discrimination and the correlated brain activation in regards to those features. Specifically, the authors aimed to determine whether phoneme discrimination based on place of articulation (PoA) elicited more activation in the motor regions than discrimination based on manner of articulation (MoA) or voicing. They also wanted to know if MoA or voicing resulted in more activation of auditory areas. Secondly, the authors sought to examine the role of attention on frontal activation. *Subjects:* This study included 47 participants (33-61 years old) who were right-handed, had typical hearing, did not have any history of neurological, psychiatric, or speech/language developmental impairments, and were not on any medication. *Methods:* Three different auditory oddball paradigms were used in this study, including three passive tasks and three active tasks. In all paradigms, the standard stimulus was the syllable /bə/. The deviant stimuli were /gə/, /pə/, and /mə/ to cover placing, voicing, and manner differences, respectively. Participants underwent a 23-channel EEG during the experiment. The data had artefacts removed and was then analyzed to determine the peak amplitudes and latencies, as well as reaction time and accuracy of responses. The time points where significant differences in activation between place, manner, and voicing stimuli occurred was used to complete source reconstruction. A default head model, including three layers to represent the scalp, skull, and brain was used for source reconstruction. This allowed for three-dimensional images that showed the evoked energy that occurred at the previously determined time points. These images allowed second level analysis to determine the following regions of interest (ROIs): inferior frontal cortex (IFC), sensorimotor cortex (SMC), inferior parietal cortex (IPC), and superior temporal cortex (STC). *Results:* Participants showed the fastest reaction times in response to MoA. All conditions elicited a significant MMN bilaterally in the anterior, central, and posterior areas. The N100 and P300 waveforms were elicited during the active tasks in response to all three contrasts. Source reconstruction of the passive tasks revealed that MoA produced higher activation slightly before the usual MMN time window in sensorimotor regions, inferior parietal regions, and superior temporal regions than PoA or voicing. Similar to the passive tasks, during the time interval from 65 to 110 ms of the active tasks showed MoA producing higher activation in the inferior frontal, sensorimotor, inferior parietal, and superior temporal regions compared to PoA. However, MoA only showed higher activation compared to voicing in sensorimotor areas. The active tasks also showed voicing to produce higher activation in inferior frontal, sensorimotor, inferior parietal, and superior temporal regions compared to PoA. During the active tasks, a later time window revealed almost the reverse results: from 130 to 175 ms, PoA produced higher activation in the inferior frontal, sensorimotor, inferior parietal, and superior temporal regions compared to MoA and voicing. From 225 to 250 ms PoA continued to show higher activation in sensorimotor and superior temporal regions compared to MoA. *Conclusions:* The authors concluded that the attention allotted to an auditory task influences the level of activation

of the frontal network in response to PoA and the auditory regions in response to MoA and voicing. The authors also suggest that early activation in the superior temporal regions in response to MoA and voicing helps facilitate phonemic discrimination. Later activation of sensorimotor areas in response to PoA are additionally important to phonemic discrimination. *Relevance to current study:* This article phonemic discrimination using ERPs and qEEG techniques to consider spatial information in regards to brain activation. This article met all the inclusion criteria and so was included in the current meta-analysis. *Level of Evidence:* IIIa.

Aisha, S., Swathi, C. S., & Vinodhini, P. (2016). Neuroimaging techniques in assessment of auditory processing disorders: A review. *Otolaryngol Open Journal*, *1,* S10-S14. http://dx.doi.org/10.17140/OTLOJ-SE-1-103

Objective: This review argued that neuroimaging should be used in the diagnosis of Auditory Processing Disorder (APD). They acknowledge that more information is needed for this to become reality and provide a summary of the studies that have been conducted with various neuroimaging techniques to examine APD. It reviews what has been found in studies that used; MRI and fMRI, MEG and EEG, and PET. *Relevance to current work:* This article provided a useful overview of multiple neuroimaging techniques used to study the auditory system.

Alain, C., Campeanu, S., & Tremblay, K. (2010). Changes in sensory evoked responses coincide with rapid improvement in speech identification performance. *Journal of Cognitive Neuroscience*, 22(2), 392–403. https://doi.org/10.1162/jocn.2009.21279

Objective: This study sought to determine if one hour of focused training on a listening task could evoke physiological changes, and if it did then would those changes be

stimulus-specific or would they generalize to other stimuli. The authors also wanted to know whether any physiological changes would coincide with perceptual changes pertaining to the experimental stimuli. *Subjects:* There were 20 participants (20-35 years old), all with normal hearing, whose data was used in the study. *Methods:* After they were presented with examples of the speech stimulus and participated in a practice session, participants were presented with series of two synthetic speech stimuli that differed in voice onset time (VOT) or a noise stimulus and asked the identify the sound with a button press. During the task, a 64-electrode EEG was recorded and the effect of rapid learning was examined through the N1 and P2 ERPs, based on data from nine frontocentral sites, as well as electrodes over the left and right temporal sites. The N2b and late positive complex (LPC) ERPs were also measured and analyzed. The amplitude, latency, and mean amplitude of the ERPs were submitted to repeated measure ANOVAs. *Results:* Behavioral data indicated that when the data was collapsed over the two speech tokens, the performance of participants slowly improved over the first four trials, and then remained stable through to the tenth trial. It was also shown that participants were fastest at identifying the noise stimulus from the phonemic stimuli. The EEG data showed that the N1 wave had a stronger response to the phonemic stimuli than the noise stimuli. Although practice did not seem to influence this ERP very much, practice-related decreases in the N1 amplitude were greater in response to noise than phonemic stimuli, and this happened more during the first four trial blocks. The P2 tended to peak earliest for the phonemic stimuli, rather than the noise stimuli, although this trend was not significant. This latency decreased as the task repetition continued, regardless of stimulus type, but it stopped decreasing after the fourth trial block. There were larger P2 amplitudes in response to the noise stimuli than the phonemic stimuli. The N2b wave showed practice effects in that the mean amplitude tended to increase with task repetition. The wave would present as more negative in response to the phonemic stimuli than the noise stimuli. Finally, the LPC wave was seen to have a larger positive response to the phonemic stimuli. Practice did not seem to largely influence the LPC response to noise, but the amplitude of the LPC in response to phonemic stimuli increased with practice. To determine the brain-behavior relationship between the change in AEP amplitude and the participants' performance, the authors computed Pearson correlation coefficients. The correlation coefficients suggested that as the auditory ERP amplitudes change, there are subsequent improvements in behavior. *Conclusions:* The authors found that this study supported previous findings that suggested that humans can learn to distinguish between subtle differences in VOT. They further suggested that rapid improvements in speech identification result from changes is various ERPs. They conclude that the underlying changes that occur that allow this learning to happen are stimulus and task specific. *Relevance to current study:* This study used auditory evoked potentials and examined aspects of phonemic discrimination. This study met all the inclusion criteria and so was included in the current meta-analysis. *Level of Evidence:* IIIa.

Bidelman, G. M., Bush, L. C., & Boudreaux, A. M. (2020). Effects of noise on the behavioral and neural categorization of speech. *Frontiers in Neuroscience*, *14,* 1-10. https://doi.org/10.3389/fnins.2020.00153

Objective: This study aimed to determine whether phonemes with strong categorical boundaries are easier to distinguish in noise than phonemes with more ambiguous boundaries. *Subjects:* The experiment included 13 participants (22-25 years old) who were all right-handed, had normal hearing, had college-level education, and had minimal, if any, musical training. *Methods:* While undergoing a 64-channel EEG, participants were presented with synthetic speech stimuli from a five-step continuum ranging from /u/ to /a/ in three noise conditions. The participants were instructed to indicate whether the stimulus they heard was an /u/ or an /a/ via button push as quickly as they could. The EEG information was cleaned, filtered, averaged, and re-referenced. The information was then applied to locations covering the whole of the scalp. The authors intended to analyze the P2 waveform but found that it occurred in a complex and so instead measured all the positive waveforms that occurred between 180 and 320 ms. The response amplitudes from continuum end points were compared to those of ambiguous and midpoint tokens in order to determine the category-related effects. Response time was also analyzed. One-way, mixed model ANOVA was used to analyze dependent measures. *Results:* Participants were best able to categorize the stimuli in clear speech, and this ability decreased as the signal-to-noise ratio (SNR) decreased. The perceptual boundary varied significantly, although marginally, in response to different noise levels. Response time was affected both by the level of noise and the stimuli; a greater response time was seen when the noise was greater than the stimulus signal and when the stimuli were ambiguous. Across noise conditions and vowel conditions, discrimination performance remained high. Electrophysiologically, the higher noise level resulted in delayed ERPs. The N1 amplitude and latency was influenced by the noise level, but not by the token. Effects from both noise and tokens were seen in the P2 wave, most prominently at the centro-parietal scalp locations. An ANOVA conducted on the ERP amplitudes showed that responses were most affected by noise, regardless of the strength of their phonetic label, although the endpoint tokens were more resilient to noise than their ambiguous counterparts. *Conclusions:* The authors found that categorical perception is robust in noise; speech was only severely degraded when the noise exceeded the speech stimuli. Additionally, they suggest that sounds with clear phonetic boundaries have enhanced neural encoding. Finally, they conclude that categorical neural representations of phonemes are more resistant to noise than more ambiguous speech sounds. *Relevance to current study:* This article explored categorical phoneme perception with EEG and ERP data while considering spatial aspects of the EEG. This study fit all the inclusion criteria and so was included in the current meta-analysis. *Level of Evidence:* IIIa.

Bidelman, G. M., & Lee, C. C. (2015). Effects of language experience and stimulus context on the neural organization and categorical perception of speech. *NeuroImage*, *120*, 191–200. https://doi.org/10.1016/j.neuroimage.2015.06.087

Objective: This study aimed to determine if proficiency in a tonal language results in faster and more accurate categorical perception compared to proficiency in non-tonal languages. *Subjects:* This study included 20 participants (21-31 years old) who were right-handed and had typical hearing. Participants had no history of psychiatric illness, and had minimal, if any, musical training. The control group consisted of 10 native English-speakers who had no significant exposure to Mandarin or any other tonal language. The experimental group had 10 Mandarin-English bilingual participants who had all grown up in mainland China and had not begun learning English until they were nine or older. The two groups were matched for age, gender, and educational levels. *Methods:* This study included two different stimuli conditions: five auditory stimuli varied equally along a continuum from Mandarin Tone 2 (T2) to Tone 3 (T3) that were presented either in the context of a neutral Tone 1 (T1) preceding or following the target stimuli. After they heard a stimuli group, participants were to push a button to indicate whether they heard T2 or T3 as quickly as possible. Participants had time to practice before the task. While completing the experimental tasks the participants underwent a 64-channel EEG. Artefacts were removed and standard processing occurred on the EEG data. A distributed source analysis was performed using sLORETA with a realistic boundary element model (BEM) volume conductor with the MNI brain. Information was gathered from a predefined ROI in the left and right primary auditory cortex, or Heschl's gyrus. Analyses was conducted on only the P2 waves. Participant's reaction times and identification accuracy were also analyzed. Mixed-model ANOVAs were conducted on the behavioral variables with group as the between-subject factor and tonal context as the within-subjects factor. *Results:* It was found that the context of stimuli (i.e., stimuli preceded or followed by T1) and the language experience of participants influenced the perceptual shift they identified in the continuum. The phoneme boundary shifted little in response to the context in the English group. However, in the Chinese group context had more of an influence on their perception of the phoneme boundary. It was also shown that the Chinese group had slower reaction times when the stimuli were near the phoneme boundary than the English group, whose reaction times did not change across the continuum. The Chinese groups had earlier latencies and stronger P2 amplitudes. Differences between current source responses showed that the Chinese group consistently had two distinct groups for T2 and T3 stimuli, whereas the English group consistently misclassified tones. *Conclusions:* The authors concluded that both context and language experience influence the auditory processing as well as the behavioral categorization of pitch. Specifically, they drew three main conclusions from their results. First, they suggested that categorical perception is influenced by the context of lexical pitch patterns, or the order in which linguistic tones occur, which those familiar with tonal languages (e.g., native Mandarin speakers) are particularly sensitive to. Secondly, they claimed that tonal language listeners had a stronger connection between brain and behavioral responses to linguistic pitch compared to non-tonal language listeners. Finally, the authors suggested that native tonal listeners (e.g., native Mandarin speakers) have a stronger and more categorical organization for pitch in the primary auditory cortex than non-tonal language listeners. *Relevance to current study:* This study uses qEEG to examine the spatial characteristics of auditory categorical perception. This study met all the inclusion criteria of the current work and so was included in the current meta-analysis. *Level of Evidence:* IIIa.

Bidelman, G. M., & Walker, B. S. (2017). Attentional modulation and domain-specificity underlying the neural organization of auditory categorical perception. *European Journal of Neuroscience*, *45*(5), 690–699. https://doi.org/10.1111/ejn.13526

Objective: This article had two primary goals: to compare categorical perception of speech and music in non-musicians and to determine the role attention plays on categorical perception. *Subjects:* This study included 10 participants (19-25 years old). Participants were right-handed, college educated, and had typical hearing. Participants were excluded if they had a history of brain injury, psychiatric problems, were familiar with any tonal languages, or had more than three years of musical training. *Methods:* Speech stimuli consisted of synthetic syllables along a five-step continuum ranging from /u/ to /a/. Musical stimuli were complex tones synthesized along a comparable continuum ranging from a minor third interval to a major third interval on the chromatic scale. The different groups of stimuli were presented separately during two different tasks. During a passive task, participants ignored the stimuli while watching a subtitled movie. In an active task, participants were asked to label a stimuli as /u/ or /a/ (in the speech blocks) or as “sad” or “happy” (in the musical blocks) as quickly as possible. During these tasks, participants were undergoing a 64-chanbel EEG. Most of the data analysis was limited to a single ROI, based on previous studies by the researchers into categorical perception, consisting of six frontal electrodes to get information on the frontocentral scalp locations. Artefacts were removed from the data and it underwent standard processing. Then scalp topographies were made and the N1 and P2 amplitudes and latencies were evaluated. Reaction times and identification accuracy of participants were also analyzed. *Results:* Behaviorally, there was an abrupt shift in categorization of the speech stimuli, compared to a more continuous categorization of the musical stimuli. Participants had slower response times when stimuli were near the perceptual boundary (i.e., more ambiguous) than when endpoint speech stimuli were presented. On the other hand, the response times for musical stimuli did not change across the continuum. The EEG data and scalp topographies showed that the N1 and P2 ERPs were strongest over the frontocentral electrodes, suggesting neural generators in the supratemporal plane. Attentional differences (i.e., active vs. passive task) did not influence N1 amplitudes in either speech or music conditions. However, the whole N1-P2 complex was influences by attentional effects. Differences between the attentional conditions were found for ambiguous speech stimuli, and stronger amplitudes were found in the passive listening task than active listening. However, the endpoint speech stimuli resulted in similar N1-P2 amplitudes across attentional conditions. The ERPs did not show passive categorical coding in the passive condition. During the musical condition, no significant effects were seen in the neural responses to attentional condition or stimulus type. A control analysis revealed that there was no association between amplitudes in response to the passive condition and behavioral categorical perception in either the speech or musical conditions. *Conclusions:* From this information, the authors concluded that non-musicians organize speech stimuli more categorically than they do musical stimuli. They also suggest that auditory categorization only occurs when an individual is actively attending to the stimuli. Finally, they concluded that the acoustic properties and category of auditory stimuli are processed within the first 200 ms of sound onset. *Relevance to current study:* This article used EEG and ERPs to study phoneme categorization while gathering spatial information using qEEG techniques. This study met all the inclusion criteria and so was included in the current meta-analysis. *Level of Evidence:* IIIa.

Bidelman, G. M., & Walker, B. (2019). Plasticity in auditory categorization is supported by differential engagement of the auditory-linguistic network. *NeuroImage*, *201*, 1-10. https://doi.org/10.1016/j.neuroimage.2019.116022

Objective: This study aimed to determine whether those who have particular training in listening (i.e. musicians) process speech in different brain regions than non-musicians. *Subjects:* This study involved 20 participants (17-26 years old), all of whom reported typical hearing and no history of neuropsychiatric illness. They were divided into groups of 10 musicians and 10 non-musicians. The groups were matched in age, educational level, and gender. *Methods:* Speech stimuli consisted of five synthetic syllables along a continuum from /u/ to /a/. Musical stimuli consisted of a similar five-step continuum of complex tones. Participants were allowed to familiarize themselves with the continuum endpoints of the musical stimuli. While a 64-channel EEG was recorded, the participants were then presented with the two groups of stimuli, ordered randomly within their groups. A button press was used to indicate whether participants heard /u/ or /a/, during the phonemic task, or a “major third” or a “minor third,” during the music task After the EEG data had any artefacts removed and it was digitally cleaned and filtered, there were 10 ERP waveforms found for each participant. The authors note that during source reconstruction the neuronal sources have to be inferred due to the nature of scalp-recorded EEG. The researchers used Classical Low Resolution Electromagnetic Tomography Analysis Recursively Applied (CLARA) to estimate current density and then recomputed with a smoother LORETA solution. Voxel size of 7 mm in Talairach space was attained. After further statistical tests, the source activations were projected onto a semi-inflated MNI adult brain template, which allowed for visualization. The CLARA analysis of activation time-course per voxel allowed the amplitude of source activation to be found in predetermined ROIs, including the bilateral primary auditory cortex (PAC) and the inferior frontal gyrus (IFG), near Broca’s area. The source amplitudes of the stimuli at the end of the continua were compared to the amplitudes from the more ambiguous, middle-continua stimuli. This allowed the researchers to determine the difference in neural activity when participants were presented with stimuli that easily fell into well-formed categories opposed to more ambiguous stimuli. *Results:* In general, musicians showed more robust cortical responses and sharper categorical boundaries than non-musicians for both speech and music stimuli. However, both groups showed stronger categorical perception for speech than for music. This was particularly noted in frontocentral electrode sites: the area where categorical perception effects are seen most prominently on the scalp. They also found differences in processing areas in musicians versus non-musicians; musicians had strong cortical responses to speech in the PAC bilaterally, whereas the cortical responses to speech in non-musicians were primarily seen in the left IFG. For musical stimuli, non-musicians had cortical responses strongest in the left precentral gyrus, which is in the motor cortex. Granger causality in conjunction with ANOVA helped to determine that the listeners' musical training, as well as the stimuli category, modulated the strength of afferent connectivity from PAC to IFG, however, no significant efferent connectivity from IFG to PAC in the left hemisphere. Overall, much stronger signaling was found from PAC to IFG than from IFG to PAC. *Conclusions:* The authors suggest that musical training leads to enhanced categorization of both musical sounds and speech sounds by restricting the perceptual space around category boundaries and allowing for more precise internal representations of auditory categories. The authors conclude that this knowledge may be helpful in treatment of disorders in which categorical perception is decreased, such as dyslexia, although they acknowledge that more research is needed in this area. *Relevance to current study:* This study used qEEG to examine the spatial characteristics of auditory categorical perception. This study met all the inclusion criteria and so was included in the current meta-analysis. *Level of Evidence:* IIIa.

Brodbeck, V., Spinelli, L., Lascano, A. M., Wissmeier, M., Vargas, M. I., Vulliemoz, S., Pollo, C., Schaller, K., Michel, C. M., & Seeck, M. (2011). Electroencephalographic source imaging: A prospective study of 152 operated epileptic patients. *Brain*, *134*(10), 2887–2897. https://doi.org/10.1093/brain/awr243

Objective: This study aimed to determine the sensitivity and specificity of multiple neuro-imaging techniques, including low- and high-resolution EEG, MRI, PET, and SPECT. It also analyzed the benefits of using an individual MRI head model in order to get accurate source localizations compared to an averaged template brain (MNI). *Study Sample:* The study included 152 patients (one to 60 years old) who were diagnosed with pharmaco-resistant focal epilepsy, whose pre-surgical evaluation had been conducted with MRI and a long-term video-EEG recording, and who were at least one-year post- and successfully responded to surgical removal of the presumed epileptic zone. *Methods:* All of the patients underwent a standard long-term video-EEG recording using 19-29 electrodes. High-resolution EEG was also collected from 55 of the patients; 40 patients had 128-electrode setups, and 14 had 256-electrode setups. All setups followed the international 10/10 system. One researcher, blind to the participants, analyzed the EEG data to find interictal epileptogenic discharges that were artefact-free. Two unblinded researchers then reviewed their analysis. Source localization was completed using the local autoregressive average (LAURA); this determines localization based on the principle that source strength decreases as distance increases. They used a simplified realistic head model in which a brain surface was taken from an MRI, the sphere that best fit the surface was calculated, and the source space was adjusted to match the ratio of the sphere radius and the actual surface radius. The researchers also conducted analyses to determine the difference between head models from real MRI and those based on template MRI. All patients had MRI scans, which were performed under standard epilepsy protocol. This imaging revealed lesions resulting from their epileptic events in 142 of the patients, and the remaining 10 had normal MRIs. Additionally, all but one patient underwent PET scans and 127 patients underwent ictal and interictal SPECT. In order to determine the effect of the brain template, the researchers compared the localization precision of individual MRI to the MNI. They also compared the localization precision based on the number of electrodes used in EEG recordings. These comparisons led to four important groups: low-resolution EEG with the MNI, low-resolution EEG with individual MRI, high-resolution EEG with the MNI, and high-resolution EEG with individual MRI. Correct localization was determined by the patient's seizures ceasing post-surgery. The researchers defined sensitivity as "the percentage of patients with focus localization within the resected zone of all patients who were seizure-free" and specificity as "the percentage of patients with focus localization outside the resected zone" in patients who experienced one to four "seizure days" a year. *Results:* High-resolution EEG with individual MRI showed the highest sensitivity and specificity, while low-resolution EEG with an MNI showed the lowest. The researchers found that high-resolution EEG with individual MRI had slightly higher sensitivity than MRI alone (84.1% vs 76.3%) and much lower specificity (87.5% vs 52.9%). Comparatively, PET had 68.7% sensitivity and 43.8% specificity while SPECT showed 57.7% sensitivity and 46.7% specificity. *Conclusions:* The best method of source localization to determine the areas of epileptic activity is high-resolution EEG recording combined with the patient's own MRI used as the head model. This method showed correct localization in 84% of 152 cases. They conclude that high-density electric source imaging that covers the whole skull is an excellent way to find the source of epileptic activity in the brain, and note that high-resolution EEG systems simplify the process and allow EEG sessions to be quick and easy, without requiring "highly experienced, well-trained personnel, expensive shielding or other inconveniences." *Relevance to Current Work:* This study was highly relevant to the current study as it directly compared EEG source localization, or its spatial resolution, to other neuroimaging techniques, particularly MRI. *Level of Evidence: IIIa.*

Brunellière, A., Dufour, S., Nguyen, N., & Frauenfelder, U. H. (2009). Behavioral and electrophysiological evidence for the impact of regional variation on phoneme perception. *Cognition*, *111*(3), 390–396. https://doi.org/10.1016/j.cognition.2009.02.013 *Objective:* This study aimed to determine whether native vowel perception is influenced by exposure to vowel mergers in a non-native accent of an individual's native language. *Subjects:* This study included 14 participants who were all French speaking with no history of hearing or neurological impairments. *Methods:* This study used the vowels /e/-/ɛ/, which are merged in Southern French but remain distinctive in mainstream French, compared to the vowels /ø/-/y/, which are stable throughout French-speaking regions. The stimuli consisted of the syllables /be/, /bɛ/, /bø/, and /by/, recorded from four female speakers and one male speaker. The best tokens of these recordings were adjusted to have the same tonal duration. During binaural stimulus presentation, the participants underwent a 64-channel EEG. In each trial, the first four stimuli were the same syllable produced by the four different female speakers, followed by the test stimuli, produced by the male speaker. The participants indicated whether the test syllable was the same or different from the context syllables through a button press. The accuracy rates and response times of participants underwent ANOVA. Electrodes were divided into six regions: frontocentral, centroparietal, left temporal, right temporal, left posterior, and right posterior. The topography and time of the EEG data helped identify three components were identified: N100, P200, and MMN. *Results:* This study showed that the

/e/-/ɛ/ contrast was behaviorally more difficult to distinguish than the /ø/-/y/ contrast. Electrophysiological results showed that there was significant differences in the processing of the two sets of vowels. The /e/-/ɛ/ contrast produced only an MMN, while the /ø/-/y/ contrast produced an MMN as well as differences between the control and deviant conditions in the P200. *Conclusions:* The authors suggest that the differences that were seen in the P200 show that earlier and easier discrimination occurs for the /ø/-/y/ contrast. They conclude that vowels that are in the process of merging are harder to discriminate, whether the contrast is preserved in an individual's accent or not. *Relevance to current study:* This study is an EEG study that looked at phonemic discrimination and processing. It considered the spatial recording of ERPs and provided topographies of the grand-average ERPs. While its spatial considerations are less specific than others are, it fit all the inclusion criteria and so was included in the current meta-analysis. *Level of Evidence:* IIIa.

Diaz, B., Baus, C., Escera, C., Costa, A., & Sebastian-Galles, N. (2008). Brain potentials to native phoneme discrimination reveal the origin of individual differences in learning the sounds of a second language. *Proceedings of the National Academy of Sciences*, *105*(42), 16083–16088. https://doi.org/10.1073/pnas.0805022105

Objective: This study aims to determine why some individuals are able to achieve native-like abilities in speaking a second language whereas others struggle to perceive and produce second language phonemes. More specifically, this study sought to determine whether second language phoneme learning is determined by general auditory processing abilities or by a speech-specific mechanism. *Subjects:* This study included 31 participants. All of the participants had normal hearing, left-hemisphere lateralization for language, and no history of language impairments, and no specific musical training. The participants were also all bilingual, from a young age, in Catalan and Spanish. The participants were divided into a 16-person “Good Perceivers” (GP) group, and a 15-person “Poor Perceivers” (PP) group based on the results of behavioral phoneme discrimination tasks. *Methods:* A passive oddball paradigm was used while the participants were undergoing an eight–channel EEG. Three conditions -- duration, frequency, and pattern -- were tested to determine general acoustic perception along with a phonemic condition to test specific language perception. The duration condition consisted of four pure-tone stimuli the standard of which was 200 ms and three deviants that were 40, 80, and 120 ms in length. The standard stimuli of the frequency condition was a 1,000 Hz pure tone, the deviant stimuli were 1,030 Hz, 1,060 Hz, and 1,090 Hz. In the pattern conditions, participants were presented with a series of two alternating pure tones in groups of six. The deviant event of the pattern was one string beginning with the same tone the previous string had ended with. The phonetic condition included a native block and nonnative block of trials. In both blocks, the standard stimulus was /o/ while the deviant in the native block was /e/ and in the nonnative block was /ö/. The ERPs were averaged separately for standard and deviant stimuli. In order to be included in analysis, deviants must have elicited a reliable MMN in at least one of the participant groups. Two repeated measures ANOVAs were completed; one included the factors laterality, frontality, central location, and deviant type while the other included the factors MMN generator, laterality, subcomponent, and participant group. *Results:* The acoustic conditions did not reveal any significant differences between the two groups. On the other hand, both deviant stimuli of the phonetic condition resulted in larger MMN amplitudes in the GP than the PP. It was also found that the MMN amplitudes were larger over central electrodes than over frontal ones. However, *post hoc* analysis showed that the GP had stronger MMN amplitudes at the frontal sites than PP. *Conclusions:* There were no differences between the groups in their abilities to process acoustic information, but when presented with a phoneme discrimination task the GP had stronger MMN responses than PP. However, this difference in MMN amplitude was only present in the frontal electrodes and not in the supratemporal ones. The authors take this to suggest that frontal MMN generators are responsible for the difference between GP and PP. This information led the authors to the conclusion that this difference in generators allows for the GP to distinguish relevant features of phonemes. The authors conclude that inborn phoneme discrimination abilities can predict the success of learning a new language. *Relevance to current study:* This article studied phoneme discrimination using EEG and the MMN while also considering the importance of the spatial distribution of the ERP. This study met all the inclusion criteria and so was included in the current meta-analysis. *Level of Evidence:* IIIa.

Jackson, A. F., & Bolger, D. J. (2014). The neurophysiological bases of EEG and EEG measurement: A review for the rest of us. *Psychophysiology*, *51*(11), 1061–1071. https://doi.org/10.1111/psyp.12283

Objective: This article was written to provide a thorough description of the neurophysiological events that lead to the electrical impulses measured by EEG, as well as other technicalities of EEG at a level to sufficiently and accurately describe the process, but not so technical that those not trained in physics can still understand it. The authors cover the neural sources of EEG, how the signal travels from brain to the recording device, as well as problems often seen in recording, and considerations when interpreting results. *Relevance to current work:* This was a useful source for the current study as it provided in-depth information on the whole process of how EEG recordings are made.

Jantzen, M. G., Howe, B. M., & Jantzen, K. J. (2014). Neurophysiological evidence that musical training influences the recruitment of right hemispheric homologues for speech perception. *Frontiers in Psychology*, *5*. https://doi.org/10.3389/fpsyg.2014.00171 *Objective:* This article set out to determine whether musicians process music and speech in similar ways. Specifically, the authors wanted to know whether right hemisphere areas associated with music processing were activated during phonemic categorization in musicians. *Subjects:* This study included 12 normal-hearing, right-handed, monolingual participants (19-22 years old), divided into groups of six musicians and six non-musicians. *Methods:* Stimuli consisted of synthetic /da/ and /ta/ syllables presented in a dichotic listening task. Participants were instructed to listen for stimuli that were presented in either the right or left ear, or told to listen for /da/ syllables or /ta/ syllables. During the tasks, EEG recordings were taken from 64 electrodes. Standardized low-resolution brain electromagnetic tomography (sLORETA) was used in conjunction with a template brain to analyze the individual EEG data of participants in order to determine source generators in Talairach coordinates. *Results:* This study found that musicians did not perform better in discriminating phonemes based on voice onset time than non-musicians. However, they did find that the musician group had much more positive P50 ERPs in the right-temporal-parietal montage, as well as greater activity in the right superior temporal gyrus (STG), and middle temporal gyrus (MTG). *Conclusions:* The authors conclude that their findings support previous research that has suggested the inclusion of the right hemisphere of the brain in speech perception. They further posit that musical training produces increased sensitivity and better selective attention to the temporal features of the speech signal, which is reflected in right hemisphere activation of the right STG and MTG during speech discrimination tasks. *Relevance to current study:* This study used a phoneme discrimination task, in conjunction with qEEG to determine information about the auditory system. It also provided strong evidence of qEEG being able to provide valuable and specific spatial information. This study fit all of the inclusion criteria and so was included in the current meta-analysis. *Level of Evidence:* IIIa.

Jin, Y., Díaz, B., Colomer, M., & Sebastián-Gallés, N. (2014). Oscillation encoding of individual differences in speech perception. *PLOS ONE*, *9*(7), e100901. https://doi.org/10.1371/journal.pone.0100901

Objective: This study used the data from the Diaz et al. article. Its purpose is similar in that it sought to determine the underlying differences between Good Perceivers (GP) and Poor Perceivers (PP) of second language. This study examined the oscillatory responses seen during the MMN during acoustic and linguistic conditions to determine any differences between GP and PP. *Subjects:* Subjects were the same as in the Diaz et al. article; 16 GP, 15 PP, all Catalan-Spanish bilinguals with normal hearing, left-hemisphere lateralization for language, and no history of language impairments, and no specific musical training. *Methods:* The stimuli that elicited an MMN in the Diaz et al. article were analyzed using event-related spectral perturbation (ERSP) and inter-trial coherence (ITC) in order to look at the neural oscillatory changes seen in the MMN. The theta, alpha, beta, and gamma frequency bands were included in the ERSP and ITC statistical analyses. *Results:* The ERSP analysis showed no significant differences between the groups during the acoustic conditions. The native deviant trials resulted in an increase in the oscillation power of the theta frequency in the GP. These differences were seen over the frontal electrodes but not over the temporal electrodes. No other frequency bands showed significant differences between the groups. No significant differences were found during the ITC analysis. The different deviant phonetic stimuli were analyzed separately and it was found that GP and PP differ primarily in their processing of native phonemes. *Conclusions:* The results of this study largely agreed with the Diaz et al. article. Their findings suggest that theta oscillations underlying the MMN are responsible for the differences between groups in native phoneme discrimination. The data showing that GP and PP differ in their processing of familiar speech sounds suggest that the GP have more efficient speech processing abilities than PP. Because the differences between theta waves were found at frontocentral electrodes and not at temporal electrodes, the authors conclude that the differences between the GP and PP groups is related more to their attentive or pre-attentive detection of signal change, rather than the comparison of sensory features. *Relevance to current study:* This study investigated phoneme discrimination while using MMN information. It also made spatial considerations based on EEG data. This study met all the inclusion criteria and so was included in the current meta-analysis. *Level of Evidence:* IIIa.

Kayser, J., & Tenke, C. E. (2006). Principal components analysis of Laplacian waveforms as a generic method for identifying ERP generator patterns: I. Evaluation with auditory oddball tasks. *Clinical Neurophysiology*, *117*(2), 348–368. https://doi.org/10.1016/j.clinph.2005.08.034

Objective: This study aimed to determine whether combining reference-free, topographically enhanced current source density (CSD) with temporal principal component analysis (PCA) would allow for the identification and measurement of the source generators of known ERP components. *Subjects:* This study included 66 adults who were right-handed and had normal hearing. *Methods:* This experiment used a set of tonal stimuli as well as two consonant-vowel syllables, /da/ and /ta/. Stimuli were presented to both ears in an active oddball paradigm. In each block of trials, participants listened to either tones or syllables and participants were instructed to respond to the deviant stimuli with either a right or left hand button or a silent count. During this time, a 30-channel EEG was recorded. Sharpened scalp topographies were produced after the recorded waveforms were smoothed and averaged, then analyzed through spherical spline current density (CSD). The waveforms were then submitted to temporal PCA to determine if there the common sources of variance in the ERP data. The reference-free transformations of the original ERP waveforms were then also submitted to temporal PCA. The different data sets, including the target stimuli and response mode as factors, were submitted to repeated measures ANOVA. *Results:* Behaviorally, it was found that participants responded faster to tonal stimuli, but more accurately to syllable stimuli. The N1, P2, P3, and slow wave were identified. The N2 and P3 waveforms were elicited only by the standard stimuli. It was found that N1 was strongest at frontocentral sites, but on average, it was smaller in response to syllable stimuli. The N2 was strongest at lateral sites, including the frontal, temporal, and parietal regions of the scalp, although it was most prominent at frontotemporal sites for tonal stimuli and temporoparietal sites for syllables. The P3 was strongest at the midparietal regions and responded more to the tonal task. The authors also found that compared to the ERP solution, the CSD solution provided sharper time courses because they resulted in less temporal overlap.

Conclusions: The authors found that using this new approach of using CSD to preprocess ERP information before submitting it to PCA allowed for better clarification and separation of the contributions of task and response mode. They suggest this as a solution to the "ubiquitous reference problem" while simultaneous reducing some of the redundancies of ERP topography. They conclude that, "the combined CSD-PCA approach shows promise as a comprehensive, generic strategy for ERP analysis."

Relevance to current study: This study used qEEG to examine the spatial characteristics of auditory categorical perception. This study met all the inclusion criteria of the current work and so was included in the current meta-analysis. *Level of Evidence:* IIIa.

Kramer, S. (2014). *Neural responses demonstrate the dynamicity of speech perception* (Unpublished master's thesis). McMaster University.

Objective: This thesis sought to determine the sensitivity of the ERP phonological mapping negativity (PMN) to coarticulation. *Subjects:* This study involved 22 participants (18-36 years old). All were native English-speakers without any history of neurological or hearing impairments. *Methods:* The stimuli included 76 commonly used, monosyllabic, CVC English words divided into sets in which the word differed only by the central vowel. All of the words used the vowels /i/, /u/, /æ/ or /ɑ/ with an anterior stop at the beginning of the word and an oral stop at the end. Stimuli were presented both auditorily and visually while the participants were undergoing a 64-channel EEG recording. Participants indicated via button-press whether the word they heard matched the word that was being shown. They were presented with words that contained coarticulation that were divided into match, mismatch, and unrelated groups. The study used the ERPs N1, P2, and phonological mismatch negativity (PMN). Each ERP component was submitted to a repeated measures ANOVA. *Results:* The researcher found that the N1 response was highly influenced by the acoustic properties of word onsets. The P2 had the strongest response to stop consonants. This ERP also showed a larger amplitude in response to trials in which the coarticulation did not match the word. The PMN proved to be sensitive to sub-phonemic congruity; words with matching coarticulation resulted in less negative sinks. It was also found that the most negative region for the PMN was frontal sites in the right hemisphere. *Conclusions:* The author suggests that the N1 is sensitive to phonemic differences. The P2 component did not react as clearly as the N1, except in the case of voicing. The PMN showed the greatest response to incongruent coarticulation. The authors note that the response of the PMN indicates sensitivity not only to within-category phonological variations, but also to between-category. The author suggests that although neurologically the participants recognized the sub-phonemic cues, they did not affect their speech processing, showing that the brains of listeners are able to recover from unexpected cues in the speech stream. They conclude that their study supports the idea that speech processing is constantly recognizing and integrating phonetic detail, and these cues influence word processing and can help with word recognition. *Relevance to current study:* This study used qEEG to examine the spatial characteristics of auditory categorical perception. This study met all the inclusion criteria of the current work and so was included in the current meta-analysis. *Level of Evidence:* IIIa.

Liebenthal, E., Sabri, M., Beardsley, S. A., Mangalathu-Arumana, J., & Desai, A. (2013). Neural dynamics of phonological processing in the dorsal auditory stream. *Journal of Neuroscience, 33*(39), 15414-15424. https://doi.org/10.1523/JNEUROSCI.1511-13.2013 *Objective:* This study used EEG and fMRI concurrently to determine the functional organization and hemispheric lateralization pattern of the dorsal auditory pathway during phonemic processing tasks by specifically looking at the timing of activation of the auditory, somatosensory, and motor regions of the brain. *Study Sample:* Behavioral and fMRI data were obtained and used from 24 participants, and ERP and joint independent component analysis (jICA) data came from 15 participants. All participants were right-handed native English speakers with no history of neurological or hearing impairments. *Methods:* A recording of the natural phoneme /ga/ was adjusted to a two-formant syllable. The second formant of this syllable was further adjusted to create a chirp and base stimuli. These stimuli were presented to different ears at the same pitch, but with different stimulus-onset-asynchronies while the participant underwent a simultaneous EEG-fMRI. Participants were either given a syllable task or a chirp task, and were to note when they heard the target stimuli by pressing one of two buttons. Within-subject analysis was then conducted by integrating the fMRI images and ERP information from 62 (of 64) of the electrodes using jICA; this method is used to help show any linear and nonlinear patterns of dependence on a variable. This created an fMRI spatial map and an ERP topographical map time series for each individual participant. After the data was smoothed, corrected, and grouped it underwent ERP source reconstruction using a threeshell sphere, Colin brain model. Seven ROIs were developed based on the areas involved in the two experimental tasks; these covered the posterior superior temporal, parietal, and precentral cortex in the left hemisphere, and was mirrored onto the right. *Results:* Stimulus-onset-asynchrony was found to only affect response time and performance accuracy during the syllable task. The authors suggest that this is because the longer beginning part of the syllable is necessary for syllable identification, not because linguistic information inherently takes longer to process than non-linguistic auditory stimuli. A comparison of the fMRI images of the two task types was made, which revealed that the syllable-onset-asynchrony had more of an effect on the syllable task than the chirp task, resulting in more activation in the left posterior temporal gyrus (pSTG), inferior parietal lobule (IPL), and ventral central sulcus (vCS). The ERPs that were elicited showed the spatiotemporal characteristics of the N1 and the P2 responses, which have been shown to be evoked by syllables, as well as the N320 and the N350 responses, which are often seen in phonological processing. The fMRI topographical maps showed that the syllable and chirp tasks generally had similar patterns of activation, and both showed strong activation in the STG, IPL, inferior frontal gyrus (IFG), supplementary motor area (SMA), and thalamus bilaterally, as well as in the left superior parietal lobule (SPL), pre- and post- central gyri. However, it was seen that the chirp task led to more activation in bilateral IPL and SPL, whereas the syllable task led to more activation in the pSTG. The findings from the ERP topographical map time series, and subsequent neural source reconstruction, varied somewhat from the fMRI findings. It showed that the syllable task had stronger activity in bilateral pSTG, and left ventral parietal and posterior frontal areas, like IPL, ventral post-central gyrus (vPostCG), and ventral pre-central gyrus (vPostCG): and the chirp task showed strong right lateralization, with greater activation in bilateral STG and in right parietal areas, such as SPL, IPL, and dorsal post-central gyrus (dPostCG). *Conclusions:* The authors conclude that order of activation of brain areas during the syllable task shows that phonological processing is less hierarchical than previously thought. They also suggest that brain areas previously not thought to be involved in phonemic perception, such as the somatomotor cortex, actually are some of the earliest involved. They report that the results of the EEG and fMRI suggest that there is a direct feedback loop beginning in the ventral parietal and ventral central sulcus and running to the posterior temporal cortex. They report that this feedback loop indicates that phonemic perception is influenced by somatosensory and articulatory representations of speech sounds. They also suggest that previous theories may have placed too much emphasize on hemispheric lateralization, and suggest that it is the functional specialization of somatosensory and motor areas that determine the dorsal auditory stream's lateralization. *Relevance to Current Work:* This article used combined fMRI-EEG to look at phonemic processing, compared to non-phonemic auditory processing, focusing heavily on the spatiotemporal properties shown by both fMRI and ERP analysis. It was helpful in that it provided information into the level of specificity that can be shown through ERP source reconstruction. *Level of Evidence: IIIa*

Maiste, A. C., Wiens, A. S., Hunt, M. J., Scherg, M., & Picton, T. W. (1995). Event-related potentials and the categorical perception of speech sounds. *Ear and Hearing*, *16*(1), 68–89. https://doi.org/10.1097/00003446-199502000-00006

Objective: This study was intended to determine whether there are physiological correlates to categorical perception. This was done using four different experiments, only the second and fourth of which will be included in this annotation. *Subjects:* The second experiment included 10 participants (21-45 years old) who were right-handed English-speakers. Similarly, the fourth experiment involved 10 participants (25-44 years old); all were right-handed English-speakers with typical hearing and no history of neurological impairments. *Methods:* The participants in the second experiment were presented six stimuli pulled from a nine-step continuum from /ba/ to /da/, with three of them closer to /ba/ and three closer to /da/. While undergoing a seven-channel EEG, the participants were given a passive auditory oddball paradigm in which they were instructed to read a book and to ignore the stimuli. The N1, P2, sustained potential (SP), and MMN were recorded and analyzed during this experiment. The amplitudes and latencies of these waveforms were subjected to repeated measures ANOVA and the scalp distributions of the ERPs were compared. During the fourth experiment, the participants underwent an 11-channel EEG, allowing for more anterior and posterior monitoring of the scalp potentials. This experiment was another passive oddball task where the participants were instructed to read a book and ignore the auditory stimuli. In one ear or the other, the participants were presented with standard stimuli /ba/ or /da/. The deviant stimuli were either the opposite phoneme to the standard, or it was the same phoneme presented at 15 dB lower. The reaction times and accuracy of the participants were subjected to repeated measures ANOVA with the conditions of the presentation ear, standard stimuli, and phonetic or intensity deviant. *Results:* The second experiment showed that the amplitudes and latencies of the N1-P2, and P1 waveforms did not greatly differ between /ba/ and /da/ standard stimuli. The MMN had the strongest amplitude when the participant was presented with across-category deviants. The scalp distribution of the MMN showed the strongest amplitude over the centroparietal regions. Analysis also showed that the N1 and SP waveforms were strongest frontocentrally. The fourth experiment showed that while there was no difference in the reaction times to phonetic versus intensity stimuli, the MMN in response to phonetic stimuli was significantly longer. The amplitude of the MMN was much larger in response to the intensity stimuli than to phonetic stimuli. There was also a stronger MMN response to the /ba/ stimuli than /da/. The fourth experiment showed some hemispheric differences based on the presentation ear, although these differences failed to reach significance. Analysis of the scalp distributions showed that the MMN in response to phonetic differences was strongest in the temporal, particularly the left, electrodes. On the other hand, the intensity differences resulted in an MMN with a supratemporal source. *Conclusions:* From the second experiment, the authors concluded that changes in speech stimuli can produce the MMN, however the amplitude of this MMN appeared smaller than MMN that occur in response to changes in intensity and pitch. They also note that the MMN in response to speech appears to be located more centroparietally than MMNs produced by other changes in stimuli. In the fourth experiment, the authors acknowledge that their EEG electrode array was too sparse to specifically determine the source of the waveforms, instead the put forward their analysis more as suggestions. They conclude that within each temporal lobe there are three sources. One source was on the supratemporal plane and helped produce the P1 and SP waveforms. Another source seemed to be located more posteriorly and contributed to the beginning of the N1 waveform. Finally, a third source was found laterally and helps produce the N1c waveform. In the fourth experiment, they found the source of the MMN that responded to intensity mismatch to be a few millimeters anterior to N1 onset main source. Overall, the study concluded that the N2-P3 complex does accurately reflect phonemic categorization; however, the changes seen in the MMN may be the result of acoustic, instead of phonetic, changes. *Relevance to current study:* This article used EEG and ERPs to study the spatial characteristics of phonemic categorization. Additionally, the second and fourth experiments in this article fit all the inclusion criteria and so were included in the current meta-analysis. *Level of Evidence:* IIIa.

Mayhew, S., Dirckx, S., Niazy, R., Iannetti, G., & Wise, R. (2010). EEG signatures of auditory activity correlate with simultaneously recorded fMRI responses in humans. *Neuroimage, 49*(1), 849-864. https://doi.org/10.1016/j.neuroimage.2009.06.080

Objective: The aim of this study was to determine whether the amplitude of auditory-evoked potentials (AEPs) are reliable electrophysiological predictors of the hemodynamic BOLD signal. The study characterized and compared single-trial measures of AEPs in the time- and time-frequency domains and investigated intra- and intersubject variability of the AEP response and how it was reflected in the BOLD signal. *Study sample:* There were 12 participants (23-32 years old), all healthy. *Methods:* Each participant underwent two sessions; one recorded AEPs with a continuous and simultaneous fMRI recorded and the other recorded AEPs without fMRI acquisition. AEPs were recorded using a 30-electrode EEG. Five measures of AEP amplitude were used; N1, P2, and time-frequency ROIs 1, 2, and 3 (TF-ROI1, 2, 3). *Results:* The authors found that time frequency amplitude of TF-ROI1 and TF-ROI 2 were significantly correlated with the BOLD signal in all bilateral auditory areas investigated. TF-ROI3 was only correlated with the BOLD signal in the anterior cingulate cortex and the supplementary motor cortex. N1 and P2 were not correlated with a BOLD signal in auditory areas, but they did correlate with a BOLD signal in bilateral pre-and postcentral gyri and the supplementary motor cortex. *Conclusions:* The authors conclude that time-frequency analysis is useful in showing EEG responses in the auditory cortex and these techniques could provide improved signal-to-noise ratios for the measurement of ERPs. *Relevance to current work:* This study took both qEEG and fMRI information and compared the findings to determine the level of agreement of source generators. *Level of evidence:* IIIa.

McPherson, D. L., Harris, R., & Sorensen, D. (2020). Functional neuroimaging of the central auditory system. In S. Hatzopoulos, A. Ciorba, & M. Krumm (Eds.), *Advances in audiology and hearing science* (Vol. 1, pp. 327–360). Apple Academic Press.

Objective: This chapter was intended to provide an introduction to functional neuroimaging, including fMRI and qEEG. It provided basic terminology needed to understand those techniques and explained the processes used to carry out the procedures. It also introduced several important considerations including analog-to-digital conversation, noise reduction, and electrodes. *Relevance to current work:* This chapter gave simple explanations of the neuroimaging techniques that were examined in the current study.

Michel, C. M. & He, B. (2019). EEG source localization. *Handbook of Clinical Neurology, 160*, 85–101. https://doi.org/10.1016/b978-0-444-64032-1.00006-0

Objective: This chapter of the *Handbook of Clinical Neurology* provides an overview of the methods used in EEG source localization. It provides information on the EEG forward problem, the inverse problem, and the many techniques that have been developed to solve it. It additionally gives information on the clinical uses of EEG, especially regarding its use in diagnosing epilepsy, determining where epileptic activity is occurring, and how it can help in determining areas for possible surgery. *Relevance to current work:* This chapter was very useful to the researcher as it provided information that was thorough, yet not overly complex, regarding the process of EEG source localization. It was also helpful in providing information on the current clinical uses of EEG.

Milner, R., Rusiniak, M., Lewandowska, M., Wolak, T., Ganc, M., Piatkowska-Janko, E., Bogorodzki, P., & Skarzynski, H. (2014). Towards neural correlates of auditory stimulus processing: A simultaneous auditory evoked potentials and functional magnetic resonance study using an oddball paradigm. *Medical Science Monitor, 20,* 35-46. https://doi.org/10.12659/MSM.889712

Objective: The aim of this study was to determine, both temporally and spatially, the neural processes and brain regions involved in processing standard and deviant auditory stimuli. *Study sample:* The study sample included six right-handed, healthy young adults with typical hearing (22-35 years old). *Methods:* Trial blocks were presented while AEPs alone were being collected and while AEPs were being collected simultaneously with fMRI data. A modified oddball paradigm was used that involved stimuli being presented in alternating standard and oddball 30-second blocks. In a session, each participant was presented with 170 standard stimuli and 30 deviant stimuli. *Results:* The results of the AEP and fMRI data were combined to obtain data with high spatial and temporal resolution. It was found that standard stimuli are processed in the primary auditory cortex, whereas deviant stimuli activated areas outside of the central auditory system, including the inferior parietal lobe, the anterior cingulate gyrus, and the insula.

Conclusions: The authors concluded that deviant stimuli are processed in cortical areas not directly related to central auditory processing and standard stimuli engage both subcortical and cortical levels of the auditory system. They also noted that combined AEP and fMRI studies could be helpful in providing clinical information about how the central auditory system functions. *Relevance to current work:* This study was helpful to the research because it provided background information on the pros and cons of qEEG and fMRI. It also provided information on the level of specificity fMRI is able to attain by measuring the brain's hemodynamic response to stimuli. *Level of evidence:* IIIa

Mulert, C., Jager, L., Schmitt, R., Bussfield, P., Pogarell, O., Moller, H. J., Juckel, G., & Hegerl, U. (2004). Integration of fMRI and simultaneous EEG: Towards a comprehensive understanding of localization and time-course of brain activity in target detection. *NeuroImage, 22*(1)*,* 83-94. https://doi.org/10.1016/j.neuroimage.2003.10.051

Objective: This study was conducted to determine if EEG data taken inside an MRI scanner was comparable to data taken outside the scanner, if information localized from EEG data coincides with fMRI localization data, and if brain regions shown to be involved in processing auditory stimuli differ in when neuro-electric activity occurs. *Study sample:* The study sample consisted of nine healthy participants (20-30 years old) with normal hearing. *Methods:* Each participant underwent an EEG session outside of the MRI scanner and a simultaneous EEG and fMRI session. In each session, they were presented with two different pure tones in a pseudo-random order, resulting in 315 non-target tones and 75 target tones in the course of five blocks. The participants were asked to press a button when they heard the non-target tone. *Results:* The authors found that inside the fMRI scanner the participants showed smaller N1 amplitudes and shorter N1 latencies, but they had comparable P3 peaks and latencies to those measured outside the scanner. They also found a high degree of agreement between fMRI- and EEG-based localizations that showed distinct patterns in the timing of activation occurring in the temporal, parietal, and frontal regions of the brain. *Conclusions:* The authors conclude that when the noise of the MRI scanner is accounted for, simultaneous fMRI and EEG studies provide valuable temporal and spatial data that could be useful in clinical evaluation of disturbed brain function. *Relevance to current work:* This study used both EEG and fMRI data to look at temporal and spatial processing of auditory stimuli. *Level of evidence:* IIIa

Nuñez, A. I. R., Yue, Q., Pasalar, S., & Martin, R. C. (2020). The role of left vs. right superior temporal gyrus in speech perception: An fMRI-guided TMS study. *Brain and Language*, *209*. https://doi.org/10.1016/j.bandl.2020.104838

Objective: The purpose of this study was to determine the areas of the brain involved in sublexical speech perception and to find a definitive causal link between those areas and phoneme perception. *Study Sample:* This study included 20 healthy participants (18-22 years old). They were right-handed, and had no history of hearing, neurobiological, or psychiatric disorders. *Methods:* Each participant underwent two separate fMRI sessions. During the first, speech and non-speech stimuli were presented in a non-word discrimination task. This fMRI data was then used to determine where speech processing was occurring in each individual. This information was used to decide the areas where Transcranial Magnetic Stimulation (TMS) would be applied to each individual to temporarily stop the functioning of a specific brain area. This second fMRI session allowed the researchers to look at phoneme processing abilities when brain areas such as the left STG, right STG, or posterior occipital lobe (serving as the control), were functioning compared to when a specific area is not functioning. *Results:* The researchers saw that there was significantly more activation in both the left STG and right STG to speech stimuli compared to non-speech stimuli. They also determined that the left anterior STG was much more involved in sublexical speech processing than the right anterior STG. In contrast, there was not a significant difference in performance seen during TMS trials that eliminated the use of the left posterior STG, right anterior STG, and control area. *Conclusions:* The authors conclude that their study supports the findings of previous studies, that the left STG is crucial in sublexical speech perception. *Relevance to current work:* This article was important to the current research as it provided recent information on the spatial information fMRI can provide. *Level of Evidence:* IIIa.

Plumridge, J. M. A., Barham, M. P., Foley, D. L., Ware, A. T., Clark, G. M., Albein-Urios, N., Hayden, M. J., & Lum, J. A. G. (2020). The effect of visual articulatory information on the neural correlates of non-native speech sound discrimination. *Frontiers in Human Neuroscience*, 14. https://doi.org/10.3389/fnhum.2020.00025

Objective: This study aimed to determine whether visual articulatory information influences the neural correlates of phonemic discrimination of non-native speech sounds. *Subjects:* The study involved 42 participants (18-40 years old). All of them were right-handed with no history of hearing or neurological impairments. They were all native English-speakers with no exposure to the dental-retroflex contrast. *Methods:* Participants were given pre- and post-test trials to determine the effect of audio-visual training. During this testing, the participants underwent a 60-channel EEG while completing an active auditory oddball task. The standard stimulus was the phoneme /ta/, while the deviants were the phonemes /ʈa/ (voiceless-plosive retroflex) and /pa/. After their pre-test, the participants were placed into one of three training conditions that the participants were pseudo-randomly chosen to receive. One group received audiovisual speech training. Another group was assigned to the incongruent-articulation condition, in which they were shown a picture of someone producing a dental sound regardless of the auditory stimuli being dental or retroflex. The last group was put in the no-articulation condition, in which they were showed a still picture of a speaker’s face with both the retroflex and dental auditory stimuli. The MMN data of each participant were averaged and formulated into topographical plots. *Results:* The MMN was elicited in all conditions. The audio-visual training condition showed a decrease in latency between the pre-test and post-test presentation of the dental-retroflex contrast. The authors did not find significant differences in MMN latency or amplitude in response to incongruent-articulation and no-articulation training conditions. The averaged MMN data showed a strong frontocentral peak in the MMN. *Conclusions:* The authors concluded that with relatively short audiovisual training, the speed that the brain can process non-native phoneme contrasts increases. However, they note that this short training session is not enough to form discrete categories for these sounds, as shown by the lack of influence the training had on the amplitude of the MMN. *Relevance to current study:* This research used EEG and the MMN to study phoneme processing and categorical perception. It used topographical plots and considered some spatial elements of the EEG. This study fit all the inclusion criteria and so was included in the current meta-analysis. *Level of Evidence:* IIIa.

Sorensen, D. O. (2018). *Cross-lingual diphthong perception: A simultaneous EEG/fMRI investigation* (Unpublished master's thesis). Brigham Young University.

Objective: This study's aim was twofold: it reviewed the research existing on perception of non-native phonemes and it conducted research exploring differences in the neural substrates and brain activity produced because of non-native phoneme perception in monolingual and bilingual individuals. *Subjects:* There were 18 monolingual, English-speaking participants (18-35 years old) that participated in a behavioral discrimination task. There were an additional 25 participants, 10 of whom were English-monolingual, 10 of whom were English-Khmer speakers who learned Khmer as adults, and five native-Khmer speakers. *Method:* The participants in the first group were given a same-different task in which they were presented with two Khmer vowels and asked to determine whether they were the same or different using a button-press. This was done over 192 trials, using eight different stimuli made of four different vowels. The response times and accuracy of each participant was then submitted to repeated measures ANOVA. The participants in the second group underwent a simultaneous EEG-fMRI. They were given a passive oddball paradigm in which they were presented with the two hardest-to-distinguish phonemes (based on the behavioral study), but told not to attend to the phonemes and instead were given silent cartoons to watch. The fMRI were co-registered and normalized into a single structural image. The data was put into a group analysis fMRI cluster image. This information was used to make a BEM head model, and sLORETA analysis was used to determine source localization. *Results:* The MMN study found that the native-Khmer participants had the MMNs with the highest amplitude and shortest latency. Repeated measures ANOVA of the averaged MMN amplitudes of the different groups did not reveal significant results, but the ANOVA for latency did. Analysis of the fMRI results showed that the task led to activity in the left STG in the native-Khmer participants, whereas the monolingual participants showed more activity in the right and left temporal lobes. The sLORETA analysis of the group MMNs did not reveal consistent source localization. *Conclusions:* This study was inconclusive in its results; possibly because of the small study size, high variance within subjects' MMNs, and/or the fMRI environment interfering with the amplitude and latency of the ERPs. However, the author notes that the results trend towards native speakers and bilingual speakers processing phonemes in the left temporal lobe, whereas monolingual individuals process phonemes in the right temporal lobe. The author concludes that more research in this area is needed to get results that are more conclusive. *Relevance to current study:* This study provided valuable information into the MMN and process of both fMRI and EEG, and the combination of the two. Despite the inconclusive findings, this thesis met all the inclusion criteria and so was included in the current meta-analysis. *Level of Evidence:* IIIa.

Strauss, A. (2015). *Neural oscillatory dynamics of spoken word recognition* (Unpublished doctoral dissertation). Max Planck Institute for Human Cognitive and Brain Sciences. *Objective:* This thesis explored the underlying neural temporal dynamics of word recognition in ideal and difficult listening conditions as measured by EEG. *Subjects:* This study included 20 participants (23-27 years old), all native German-speakers, right-handed, with typical hearing, and with no history of language or neurological disorders. *Methods:* The stimuli were divided into four conditions: real, ambiguous, opaque, and filler. The real words consisted of 60 tri-syllabic concrete German nouns. These nouns were converted into the ambiguous and opaque pseudo-words. Ambiguous pseudo-words had the vowel of the second syllable replaced with another vowel to produce a word in which the original word was the only real neighbor. Opaque pseudo-words were tri-syllabic amalgamations of syllables across words. An additional 60 real words were used as fillers to allow for a balance between real words and pseudo-words, but the responses to these words were not analyzed further. While undergoing a 64-channel EEG, participants were given a lexical decision task in which they were asked to listen to the stimuli presented to them and to indicate via button press whether they heard a German word or not. Response times and accuracy scores were gathered and analyzed. The N1-P2 complex and a later N400-like deflection were analyzed. Artefacts were removed from the EEG data and it was processed and re-referenced to get “clean data.” Auditory ERPs were collected from the pre-determine ROI over the midline electrodes. Time series analysis was performed on the ERP amplitudes, and a repeated measures ANOVA was conducted with factors for wordness (i.e., real, ambiguous, or pseudo). The adaptive spatial filter Dynamic Imaging of Coherent Sources (DICS) was used for source imaging. A standard MRI template was used to make a three-layer boundary elements model (BEM) on which the electrode locations were co-registered. Further processing occurred to spatially normalize the data to MNI space, average it across participants, and show the information on an MNI template. *Results:* The participants overall showed high accuracy regardless of the wordness condition. However, they were least accurate in differentiating ambiguous pseudo-words from real words and most accurate at differentiating opaque pseudo-words from real words. A typical N1-P2 complex, followed by a N400-like deflection were observed in response to all conditions. However, a repeated measure

ANOVA showed amplitudes that were significantly different between conditions at 0.5 to 1.2 seconds. Further analysis of the amplitudes showed that over the whole time course, the opaque stimuli showed higher amplitudes than real words; the ambiguous stimuli initially had stronger amplitudes than real words, but later in the time-course decreased to the same level as real words; and opaque stimuli resulted in higher amplitudes than ambiguous stimuli. Analysis of the response of the alpha oscillations to ambiguity effects showed significant differences between all three conditions over the left frontal and bilateral central electrodes. Analysis of theta oscillations in response to ambiguity effects for differences at the left-central anterior electrodes and the parietal electrodes. No significant differences between the ambiguous and real words in the theta range were found. Source projections of the alpha oscillations in response to wordness effect showed the strongest activation at the right dorsolateral prefrontal cortex (BA 9), but extended into the right somatosensory areas, premotor cortex, bilateral ventral and dorsal anterior cingulate cortex, and right inferior prefrontal gyrus, including pars triangularis (BAs 3, 6, 4, 24, 32, 47, and 45, respectively). There was another peak in activation in the left occipital temporal cortex that extended into the fusiform gyrus, inferior temporal gyrus, and middle temporal gyrus (BAs 37, 20, and 21). Source projections of the theta oscillations in response to wordness effect showed at least two possible generators. Peak activation was seen left anteriorly in pars opercularis (BA 44) and extended into the left dorsolateral prefrontal cortex and premotor cortex (BAs 9/46 and 6). Another area of strong activation was seen in the right middle temporal gyrus (BA 21), fusiform gyrus (BA 37), supramarginal gyrus (BA 40), and posterior STG (BA 21). *Conclusions:* The alpha oscillations had the strongest response to opaque pseudo-words and the weakest response to real words. This led the authors to conclude that ambiguity results in poor lexical integration. They also suggested that the increase in theta oscillations in the left inferior frontal gyrus and right middle temporal gyrus in response to ambiguous stimuli was the brain's attempt to resolve lexical ambiguity by replaying the relevant lexico-semantic information. *Relevance to current study:* While this study aimed to find information on lexical processing rather than phonemic categorization or discrimination, a significant portion of their stimuli were changed from other stimuli by a single phoneme. This study used ERPs (and ERP subcomponents) to explore the underpinnings of the auditory system. It met all the inclusion criteria and so was included in the current meta-analysis. Additionally, this dissertation provided useful information on how qEEG works. *Level of Evidence:* IIIa.

Szymanski, M. D., Yund, E. W., & Woods, D. L. (1999). Human brain specialization for phonetic attention. *NeuroReport*, *10*(7), 1605–1608. https://doi.org/10.1097/00001756-199905140-00039

Objective: This study was meant to examine the effects auditory selective attention has ERPs seen in response to speech sounds. *Subjects:* This study included 13 participants (20-29 years old), with normal hearing. *Methods:* This experiment included a dichotic listening oddball task completed while undergoing a 30-channel EEG. The standard stimulus was the VCV syllables /ibi/, produced by a male voice in the right ear and a female voice in the left ear. The deviant stimuli consisted of the syllables /igbi/, /ibgi/, and /igi/. Deviants in which the intensity of a consonants was increased were also included. Each type of stimulus was presented binaurally, but participants were instructed to listen only for stimuli in a given ear. They listened for a target deviant and acknowledged it with a button press. The Nd waveform was measured and analyzed. *Results:* Behaviorally, the authors found that reaction time did not differ greatly between the conditions, although participants were slightly more likely to push the button during the phonemic condition. The Nd waveform was found over posterior frontal sites in both the left and right hemispheres. Attention effects were significant between 100 to about 500 ms. The phonemic condition resulted in stronger Nd amplitude than the intensity condition. Earlier Nd waves occurred over central scalp locations, but the later Nd waves had a frontal distribution. The later scalp distributions showed a tendency to be more left dominant during the phoneme condition. *Conclusions:* The authors concluded the selective attention does influence the Nd wave during phonemic discrimination tasks. They also noted that in the early Nd, processing was bilateral, suggesting that there are phoneme processing mechanisms in both the left and right hemispheres, however the left hemisphere has specialized mechanisms for the later stages of phoneme analysis. *Relevance to current study:* This study it used EEG and ERPs to learn about phoneme discrimination while considering spatial information. This study fit all the inclusion criteria and so was included in the current meta-analysis. *Level of Evidence:* IIIa.

Turkeltaub, P. E., & Coslett, H. B. (2010). Localization of sublexical speech perception components. *Brain and Language*, *114*(1), 1-15. https://doi.org/10.1016/j.bandl.2010.03.008

Objective: This meta-analysis aimed to determine the precise anatomic locations of sublexical processes involved in speech perception. The goal most related to the current work was to determine specific areas that are involved in categorical phoneme perception. *Study Sample:* The article consisted of two meta-analyses, the second of which was most relevant to the current thesis; its purpose was to determine the specific brain areas involved in categorical perception. Eight studies were included in the meta-analysis, including 123 participants. *Methods:* Studies that were included needed to have used either fMRI or PET to gather data from healthy, right-handed adults. The experiments conducted needed to have used natural or synthetic speech stimuli to tests participants' categorical perception abilities and focused on identifying brain areas involved in categorical phoneme perception. The experiments then needed to present the results in a stereotactic 3D coordinate system. The meta-analysis did not include studies that were case reports of single-subjects, used pre-specified ROIs, or conducted phoneme discrimination experiments in which the choice of speech categories made difficult to determine which condition was the independent variable and which was the control. When all the included articles had been identified, the data underwent the standard Activation Likelihood Estimation (ALE) analysis technique. Resulting MNI coordinates were converted into Talairach coordinates. Based on the Talairach coordinates, and their visualization onto the Colin brain, Brodmann's areas were assigned, using a plus or minus of two mm search cube, or the nearest gray matter. *Results:* Their analysis resulted in two significant activation clusters: the left supramarginal gyrus (BA 40) and the left anterior gyrus (BA 39/7). The authors note, however, that two of the eight articles included in the meta-analysis drove this data, and so their results do not indicate agreement across all the relevant previous literature. *Conclusions:* The authors conclude that the role the left SMG and AG play in categorical perception of phonemes is not clear and that more research into the subject is needed. *Relevance to Current Work:* This article it provided the results of eight previous fMRI categorical perception studies and provided spatial information from fMRI studies that can be compared to the information gathered from the qEEG studies included in this meta-analysis. *Level of Evidence: Level I.*

Wagner, M., Shafer, V. L., Martin, B., & Steinschneider, M. (2012). The phonotactic influence on the perception of a consonant cluster /pt/ by native English and native Polish listeners: A behavioral and event related potential (ERP) study. *Brain and Language*, *123*(1), 30–41. https://doi.org/10.1016/j.bandl.2012.06.002

Objective: This study was intended to determine whether phoneme perception is dependent on whether a phonotactic pattern is present in an individual's language repertoire. The authors additionally examined the effect the lack of an onset cluster had on the ERP time-course of speech processing. *Subjects:* This study included 24 participants: 12 native Polish speakers (23-34 years old) and 12 native English speakers (21-35 years old). The participants all had typical hearing, were right handed, and did not have a history of any speech/language, cognitive, or neurological impairments. *Methods:* While undergoing a 65-channel EEG, participants were presented with a series of two- and three-syllable nonsense words beginning with /pt/, /pət/, /st/ and /sət/. The stimulus onset /pt/ was chosen because it is an acceptable initial cluster in Polish but not in English. The stimuli were placed into word pairs matched for rhyme. Each word pair either consisted of two stimuli that were the same or two stimuli that were different. For each stimuli the participant had to indicate via button push whether the second nonsense word in the pair had two or three syllables. Time intervals of interest were determined through global field power (GFP). Brain Electric source Analysis (BESA) was used to make current source density (CSD) maps to identify the spatial areas that correlated with these time intervals. *Results:* The Polish and English speakers were both able to identify two- and three-syllable /st/ words accurately and with ease. The Polish speakers were able to accurately indicate the syllable count of the /pt/ words, but all but one of the English-speaking participants were not able to do so. Two peaks of brain activity were found in response to the /st/ and /pt/ contrasts. The first peak occurred between 232 and 424 ms and seemed to show more negativity in the temporal regions and more positivity in the frontocentral regions. The later peak occurred between 424 and 712 ms and was related to posterior parietal activity. *Conclusions:* The authors found that Polish listeners were able to distinguish between nonsense words beginning with /pt/ and /pət/ while English speakers were not. The authors conclude that this finding suggests that exposure to phoneme strings in specific contexts are necessary for accurate perception. However, there was evidence found in the ERPs that discrimination of /pt/ and / pət/ occurred in English speakers although they were unable to perceive the difference. The authors take this to indicate that the brain notices acoustic differences in sound sequences, even if there is not conscious perception of a difference. *Relevance to current study:* This article used EEG and ERPs to investigate phoneme discrimination abilities. It additionally used qEEG techniques to gather spatial information. This study fit all the inclusion criteria of the current work and so was included in the current meta-analysis. *Level of Evidence:* IIIa.

APPENDIX B

Coding Sheet

The tables included in this appendix represent the coding sheet completed while finding the articles included in this meta-analysis. At the time of coding, this was completed on an Excel sheet, but for spacing purposes the sheet was divided into four tables. Table B1 represents the basic publication characteristics, such as the title, author, language of publication and language(s) used in the experiment, and publication status. Table B2 shows the participant characteristics, such as the sample size, number of males to females, and participant health. Table B3 represents the experiment characteristics, such as the number of electrode channels used, ERPs measured, and brain areas discussed. For ease of reading, Table B4 is presented as three charts; it provides the coding abbreviations that were used in Table B3.

Table B1

Publication Characteristics

Title	Author	Year	Language	Place	Organization	Type of Publication	Peer-Reviewed
Spatiotemporal differentiation in auditory and motor regions during auditory phoneme discrimination.	Aerts et al.	2017	English/Dutch	Belgium	U Ghent University	J	Y
Cross-lingual diphthong perception: A simultaneous EEG/fMRI investigation	Sorensen	2018	English	Utah, USA	U Brigham Young University	D	N
Neurophysiological evidence that musical training influences the recruitment of right hemispheric homologues for speech perception	Jantze et al.	2014	English	Washington, USA	U Western Washington University	J	Y
Behavioral and electrophysciological evidence for the impact of regional variation on phoneme perception	Brunelliere	2009	English/French	Switzerland	U University of Geneva	J	Y
Principal components analysis of Laplacian waveforms as a generic method for identifying ERP generator patterns: I. Evaluation with auditory oddball tasks	Kayser & Tenke	2006	English	New York, USA	U Columbia University	J	Y
The phonotactic influence on the perception of a consonant cluster /pt/ by native English and native Polish listeners: a behavioral and event related potential (ERP) study	Wagner et al.	2012	English	New York, USA	U St. John's University	J	Y
Plasticity in auditory categorization is supported by differential engagement of the auditory-linguistic network	Bidelman & Walker	2019	English	Tennessee, USA	U University of Memphis	J	Y
Attentional modulation and domain specificity underlying the neural organization of auditory categorical perception	Bidelman & Walker	2017	English	Tennessee, USA	U University of Memphis	J	Y
Neural oscillatory dynamics of spoken word recognition	Strauss	2015	German	Germany	C Max Planck Institute for Human Cognitive and Brain Sciences / U Leipzig University	D	N
Effects of language experience and stimulus context on the neural organization and categorical perception of speech.	Bidelman & Lee	2015	English/Mandarin	Tennessee, USA	U University of Memphis	J	Y
Oscillation encoding of individual differences in speech perception	Jin et al.	2014	Spanish/Catalan	Barcelona, Spain	U Pompeu Fabra University	J	Y
Brain potentials to native phoneme discrimination reveal the origin of individual differences in learning the sounds of a second language	Diaz et al.	2008	Spanish/Catalan	Barcelona, Spain	U University Barcelona	J	Y
The effect of visual articulatory information on the neural correlates of non-native speech sound discrimination	Plumridge et al.	2020	English	Australia	U Deakin University	J	Y
Event-related potentials and the categorical perception of speech sounds (Experiment 2)	Maiste et al.	1995	English	Ottawa, Canada	G National Research Council Canada / U University of Ottawa	J	Y
Event-related potentials and the categorical perception of speech sounds (Experiment 4)	Maiste et al.	1995	English	Ottawa, Canada	G National Research Council Canada / U University of Ottawa	J	Y

Title	Author	Year	Language	Place	Organization	Type of Publication	Peer-Reviewed
Neural responses demonstrate the dynamicity of speech perception	Kramer	2014	English	Ontario, Canada	U McMaster University	D	N
Changes in sensory evoked responses coincide with rapid improvement in speech identification performance	Alain et al.	2010	English	Toronto, Canada	U University of Toronto	J	Y
Effects of noise on the behavioral and neural categorization of speech	Bidelman et al.	2020	English	Tennessee, USA	U University of Memphis	J	Y
Human brain specialization for phonetic attention	Szymanski et al.	1999	English	California, USA	U University of California, Davis	J	Y

Note. U = university; C = contract research firm; G = government entity; J = journal; D = dissertation or thesis; Y = yes; N = no

Table B2

Participant Characteristics

Article	Sample Size	Male	Female	Age Range	Right-Handed	Hearing	Healthy
Aerts et al., 2017	47	23	24	33.83-61.45	Y	T	Y
Sorensen, 2018	25	-	-	18-35	-	-	-
Jantzen et al., 2014	12	-	-	19-22	Y	T	-
Brunelliere, 2009	14	-	-	-	Y	T	Y
Kayser & Tenke, 2006	66	25	41	20-51	Y	T	Y
Wagner et al., 2012	24	8	16	21-35	Y[a]	T	Y
Bidelman & Walker, 2019	20	5	15	17.9-26.9	Y[b]	T	Y
Bidelman & Walker, 2017	10	1	9	19.7-25.3	Y	T	Y
Strauss, 2015	20	10	10	23.6-27.6	Y	T	Y
Bidelman & Lee, 2015	20	10	10	21.8-31.5	Y	T	Y
Jin et al., 2014[c]	31	4	27	20-26	Y[b]	T	Y
Diaz et al., 2008	31	4	27	20-26	Y[b]	T	Y
Plumridge et al., 2020	42	12	30	18-40	Y	T	-
Maiste et al., 1995 (ex. 2)	10	5	5	21-45	Y	-	-
Maiste et al., 1995 (ex. 4)	10	5	5	25-44	Y	T	Y
Kramer, 2014	22	8	14	18-36	-	T	Y
Alain et al., 2010	20	9	11	20-35	-	T	-
Bidelman et al., 2020	15	3	12	22.6-26	Y	T	-
Szymanski et al., 1999	13	5	8	20-39	-	T	-

Note. Y = yes ; T = typical

[a] 3 participants were left-handed [b] 1 participant was left-handed [c] Jin et al. 2014 used the MMN data from Diaz et al. 2008 to further investigate the spectral dynamics of phoneme learning.

Table B3

Experiment Characteristics

Article	Phonemes Used	Paradigm	Task	qEEG	Number of Channels	Head Model	Individual ERP	ERP Complexes	ROIs/Brain Areas Discussed
Aerts et al., 2017	/bə/ /gə/ /pə/ /mə/	O	A/P	BrainVision Analyzer 2	23	M, B	1, 9, 4	4	303, 311, 318, 320
Sorensen, 2018	/aə/ /aw/	O	P	sLORETA	64	B	1	-	205, 206, 209, 201, 204
Jantzen et al., 2014	/dɑ/ /tɑ/	D	A	sLORETA	64	T	7, 9, 3	2	R320, 321
Brunelliere, 2009	/be/ /bɛ/ /bø/ /by/	O	A	-	64	-	9, 3, 1	-	105, 102, L112
Kayser & Tenke, 2006	/da/ /ta/	O	A	PCA	31	S	9, 3, 10, 4, 14, 18	5	102, 118, 112, 106, 110, 110, 111, 210, 208, 109, 202, 104, 215, 117
Wagner et al., 2012	/pt/ /pət/ /st/ /sət/	O	A	CSD	65	C	17, 19, 6	-	102, B114, B115, R109
Bidelman & Walker, 2019	5 stimuli along continuum /u/ to /a/	O	A	CLARA, LORETA	64	M	2, 9, 3	1	324, L303, L313
Bidelman & Wallker, 2017	5 stimuli along continuum /u/ to /a/	O	A/P	PCA	64		9, 3	3	102
Strauss, 2015	3-syllable words and pseudowords differing by /i/ /e/ /a/ /o/	O	A	DICS	64	B, M	9, 3, 17	3	L303, B306, R308, 312, 316, 317, 304, 313, L329, 331, L322, R321, 327, 320
Bidelman & Lee, 2015	5-step continuum Mandarin T2 to T1	O	A	PCA, sLORETA	64	B, M	3	-	324, 325
Jin et aal., 2014	/o/ /e/ /ö/	O	P	ICA	8	-	1	-	102, 112, 107
Diaz et al., 2008	/o/ /e/ /ö/	O	P	ICA	8	-	1	-	104, 101, 113
Plumridge et al., 2020	/ta/ /ʈa/ /pa/	O	P	ICA	60	-	1	-	102
Maiste et al., 1995 (Ex. 2)	6 stimuli from 9-step continuum from /ba/ to /da/	O	P	-	10	-	1, 2, 9, 3, 20	-	105, 102

Article	Phonemes Used	Paradigm	Task	qEEG	Number of Channels	Head Model	Individual ERP	ERP Complexes	ROIs/Brain Areas Discussed
Maiste et al., 1995 (ex. 4)	/ba/ /da/	O	P	-	14	-	1, 9, 20	-	337, 202, 112
Kramer, 2014	CVC words differing by /u/ /i/ /æ/ /ɑ/ spliced with congruent or incongruent coarticulatory cues	Forced Choice	A	Brain Vision Analyzer 2	64	-	13, 9, 3	-	102
Alain et al., 2010	2 /ba/ stimuli, differing in VOT	O	A	BESA, PCA	64	-	9, 3, 11, 19	-	B202, 207, R112, L112, R324, R116, L116
Bidelman et al., 2020	5-step continuum from /u/ to /a/	O	A	BESA, PCA	64	-	9, 3, 5	-	105
Szymanski et al., 1999	/ibi/ ibgi/ /igbi/ /igi/	D	A	-	30	-	8	-	103, 104, 101

Note. O = oddball; D = dichotic listening task; A = active; P = passive; M = MNI brain; B = BEM; T = Talairach template; S = 2D-representation of spherical spline surface interpolation; C = CSD topographical maps

Table B4

Key for Coding Terms

ROIs/ Brain Areas Discussed				
General Term	Electrode Sites	General Regions	Specific Areas	
B= bilateral	101= frontal	201= frontal	301= middle frontal gyrus	319= superior parietal lobe
R= right	102= frontocentral	202= frontal-central	302= orbitofrontal area	320= superior temporal gyrus
L= left	103= posterior frontal	203= central	303= inferior frontal gyrus	321= middle temporal gyrus
	104= central	204= parietal	304= Broca's area	322= inferior temporal gyrus
	105= centroparietal	205= frontal parietal	305= pars orbitalis	323= posterior temporal gyrus
	106= parietal	206= centroparietal	306= dorsolateral/ prefrontal cortex	324= primary auditory cortex
	107= frontoparietal	207= parietal-occipital	307= anterior prefrontal cortex	325= Heschl's gyrus
	108= midparietal	208= temporoparietal	308= primary somatosensory cortex	326= Wernicke's area
	109= posterior parietal	209= temporal	309= ventral post-central gyrus	327= supramarginal gyrus
	110= lateral temporoparietal	210= fronto/anterior temporal	310= dorsal post-central gyrus	328= angular gyrus
	111= centro-temporo-parietal	211= middle temporal	311= sensorimotor cortex	329= occipital temporal cortex
	112= temporal	212= posterior temporal	312= premotor supplementary motor cortex	330= middle occipital gyrus
	113= supratemporal	213= supratemporal	313= primary motor cortex	331= fusiform gyrus
	114= anterior temporal	214= lateral temporal	314= ventral pre-central cortex	332= parahippocampus
	115= posterior temporal	215= somatosensory	315= dorsal pre-central gyrus	333= thalamus
	116= cerebellar		316= ventral anterior cingulate cortex	334= hypothalamus
	117= occipital		317= dorsal anterior cingulate cortex	335= subgenual area
	118= laterofrontal		318= inferior parietal cortex	336= retrosplenial cortex
				337= supratemporal plane

Individual ERPs		
1= MMN	8= Nd	15= N320
2= P100	9= N100	16= N350
3= P200	10= N200	17= N400
4= P300	11= N2b	18= Slow Wave
5= P3b	12= N240 (Release Component)	19= Late Positive Complex
6= P400	13= N280 (Phonological Mapping Negativity)	20= Sustained Potential
7= P50m	14= N300	

ERP Complexes
1= P1/N1/P2
2= P50/N1/P2
3= N1/P2
4= N1/P3
5= N2/P3