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Elucidating an implicit learning network in healthy adults during artificial grammar tasks

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Elucidating an implicit learning network in healthy adults during artificial grammar tasks

By

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Table 1. Papers included in the meta-analysis, with relevant study characteristics

Time of Scan	**Author (Year)**	**Participants N (F)**	**Age (Mean ± SD)**	**Type of Grammar**	**Rule Type**	**Feedback**	**Stimulus Presentation**	**Included Contrasts (Grammatical)**	**Included Contrasts (Ungrammatical)**
Learning									
	Fletcher et al. (1999)	7 (3)	28 (nr)	Artificial grammar	Linear (Finite state)	Yes	Visual	learn > baseline learn > baseline	
	Karuza et al. (2013)	25 (17)	20.5 (nr)	Artificial language	Transitional probabilities	No	Auditory + Visual	learn > baseline learn > baseline	baseline > learn
	Karuza et al. (2016)	16 (10)	20.7 (1)	Artificial language	Transitional probabilities	No	Auditory	learn > baseline learn > baseline	
	Opitz & Friederici (2003)	14 (7)	25 (nr)	Artificial grammar	Phrase structure (BROCANTO)	Yes	Visual	learn > baseline	
Test									
	Bahlmann et al. (2008)	14 (7)	25.5 (3.7)	Artificial grammar	Hierarchical and adjacent	Yes	Visual	test > test	test > test
	Conway et al. (2020)	21 (12)	22.1 (nr)	Artificial grammar	Adjacent and non-adjacent	No	Visual		test > test test > test
	Finn et al. (2013)	10 (5) 10 (5)	24.5 (5) 24 (5.3)	Artificial language	Phrase structure	No	Auditory + Visual	test > baseline test > baseline	
	Folia & Petersson (2014)	32 (16)	nr, range = 19-27	Artificial grammar	Linear (Reber finite state)	No	Visual		test > test test day 5 > test day 1
	Forkstam et al. (2006)	12 (8)	23 (3)	Artificial grammar	Linear (Reber finite state)	No	Visual	test > baseline test > test day 8 test > test day 1 (balanced for ACS) test > test day 8 (balanced for ACS)	test > test day 1 test > test day 8 test > test day 1 (balanced for ACS) test > test day 8 (balanced for ACS)
	Hauser et al. (2012)	17 (7)	24 (nr)	Artificial grammar	Phrase structure (BROCANTO)	Yes	Visual	test > test	
	Lieberman et al. (2004)	9 (5)	nr, range = 20-32	Artificial grammar	Linear (Markovian finite state)	Yes	Visual	test > test	

Table 1. Continued

Time of Scan	Author (Year)	Participants N (F)	Age (Mean ± SD)	Type of Grammar	Rule Type	Feedback	Stimulus Presentation	Included Contrasts (Grammatical)	Included Contrasts (Ungrammatical)
Test (cont.)	Morgan-Short et al. (2015)	13 (6)	21.8 (2.2)	Artificial grammar	Phrase structure (Brocanto2)	Yes	Auditory + Visual	post test > pre test test > baseline test > baseline	
	Newman-Norlund et al. (2006)	18 (10)	nr, range = 18-21	Artificial language	Linear (Finite state)	Yes	Auditory	post test > pre test	
	Petersson et al. (2004)	12 (3)	24 (3)	Artificial grammar	Linear (Reber finite state)	No	Visual	test > baseline test > test test > baseline	test > test
	Seger et al. (2000)	14 (3)	nr	Artificial grammar	Linear (Finite state)	No	Visual	test > baseline test > baseline test > baseline	
	Skosnik et al. (2002)	23 (11)	nr	Artificial grammar	Linear (Markovian finite state)	No	Visual	test > test test > test	
	Thiel et al. (2003)	16 (7)	30 (nr)	Artificial grammar	Chunk-based	No	Visual		test > test
	Wilson et al. (2015)	12 (6)	23 (nr)	Artificial grammar	Linear (Finite state)	No	Auditory		test > test
	Yang & Li (2012)	43 (21)	21.6 (2.6) 20.4 (1.1)	Artificial grammar	Linear (Markovian finite state)	No	Visual	test > rest test > rest	
	Yusa et al. (2011)	36 (nr)	21.6 (1.6)	Non-native language	English negative inversion rule	Yes	Auditory + Visual	test 2 > test 1	test 2 > test 1
Learning + Test									
	Goranskaya et al. (2016)	61 (31)	26.9 (3.8)	Artificial grammar	Pairwise dependencies	No	Auditory	learn + test > baseline	
	McNealy et al. (2006)	27 (13)	26.63 (nr)	Artificial language	Transitional probabilities	No	Auditory	learn > rest test > baseline test > baseline	baseline > learn

Table 1. Continued

Time of Scan	**Author (Year)**	**Participants N (F)**	**Age (Mean ± SD)**	**Type of Grammar**	**Rule Type**	**Feedback**	**Stimulus Presentation**	**Included Contrasts (Grammatical)**	**Included Contrasts (Ungrammatical)**
Learning + Test (cont.)	Ordin et al. (2020)	24 (14)	25.5 (3.3)	Artificial language	Transitional probabilities	No	Auditory	test > test test > test	learn > learn
	Tettamanti et al. (2002)	14 (7)	27.2 (nr)	Artificial grammar	Hierarchical and non-hierarchical	No	Visual	learn > baseline learn > baseline	baseline > learn
	Turk-Browne et al. (2009)	16 (9)	23 (nr)	Non-native language	Transitional probabilities	No	Visual	learn > learn	

*ACS= associative chunk strength

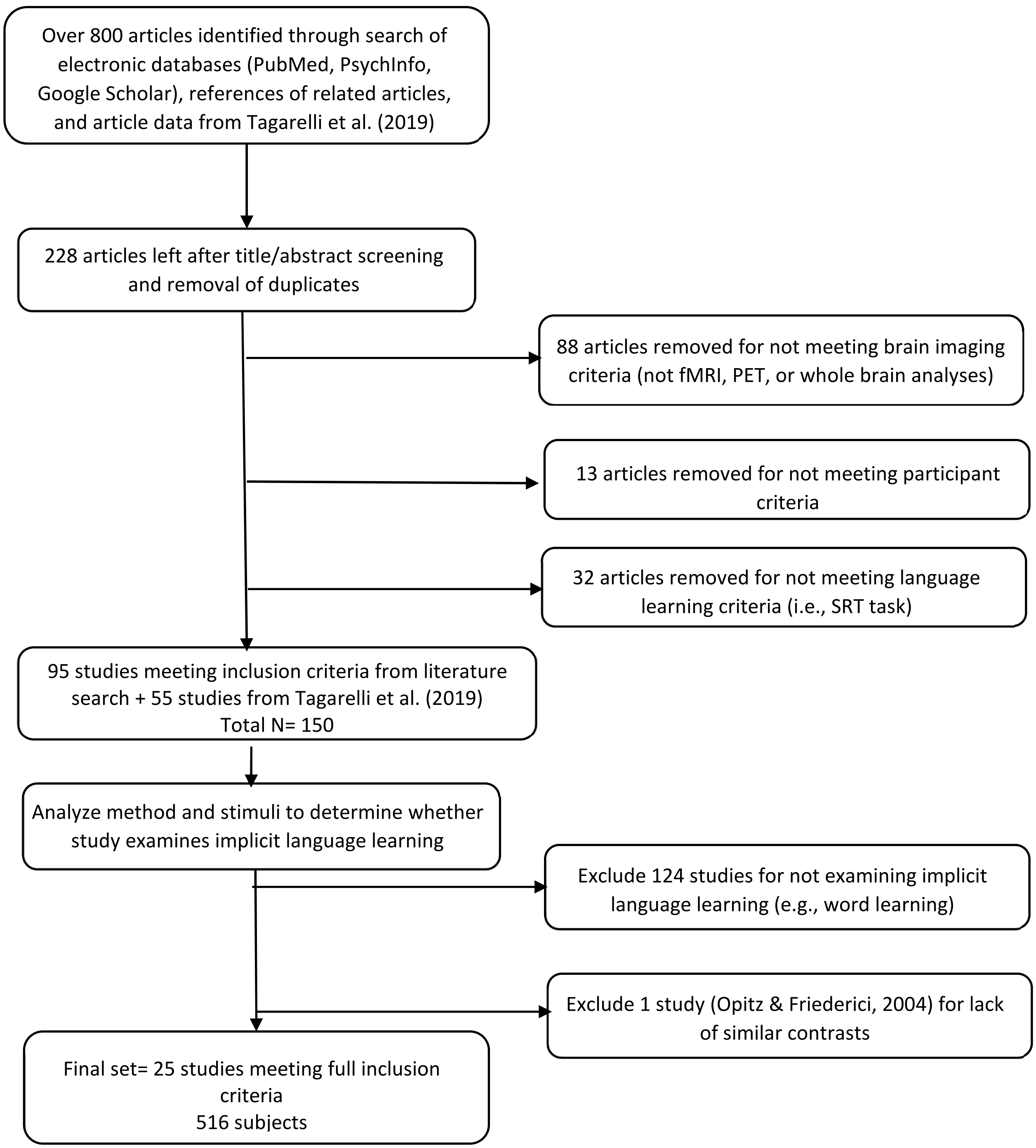
Table 2. Results for pooled Grammatical + Ungrammatical ALE analyses (ALE Max= Z-score)

ALE Group	Cluster	X	Y	Z	Volume (mm^3)	ALE Max	Label
Pooled (Grammatical + Ungrammatical)	1	-44	12	20	12352	7.36	L Inferior Frontal Opercularis
	1	-34	22	-2	12352	7.26	L Insula
	2	48	26	20	5392	5.73	R Inferior Frontal Triangularis
	2	50	26	4	5392	4.69	R Inferior Frontal Triangularis
	2	48	4	30	5392	3.32	R Precentral Gyrus
	3	6	26	34	3952	5.79	R Middle Cingulate Gyrus
	3	2	22	50	3952	4.99	L Supplemental Motor Area
	4	36	22	-4	2584	7.29	R Insula
	5	32	-66	38	1264	5.52	R Middle Occipital Gyrus
	6	36	-50	48	1104	4.02	R Inferior Parietal Lobule

Table 3. Results from ALE analyses of Grammatical group, Ungrammatical group, and their conjunction (ALE Max= Z-score)

ALE Group	Cluster	X	Y	Z	Volume (mm^3)	ALE Max	Label
Grammatical	1	-46	8	14	6096	5.08	L Inferior Frontal Opercularis
	1	-46	28	28	6096	4.84	L Inferior Frontal Triangularis
	1	-46	2	30	6096	4.15	L Precentral Gyrus
	2	-30	22	-2	1536	6.45	L Insula
	3	32	-72	38	976	4.47	R Middle Occipital Gyrus
	4	34	24	0	888	4.63	R Insula
	5	-42	-28	10	832	4.55	L Superior Temporal Gyrus
Ungrammatical							
	1	-44	12	22	7504	6.56	L Inferior Frontal Opercularis
	1	-38	20	0	7504	5.78	L Insula
	2	48	26	18	6560	6.21	R Inferior Frontal Triangularis
	2	48	18	42	6560	4.88	R Middle Frontal Gyrus
	2	46	32	-4	6560	3.33	R Inferior Frontal Orbitalis
	3	6	26	32	3224	5.31	R Middle Cingulate Gyrus
	3	0	24	52	3224	4.40	L Supplemental Motor Area
	4	36	22	-4	1856	7.00	R Insula
Conjunction							
	1	-44	10	18	1856	4.74	L Inferior Frontal Opercularis
	1	-44	26	22	1856	3.74	L Inferior Frontal Triangularis
	2	-34	20	-2	520	5.02	L Insula

Figure 1. PRISMA flowchart showing the literature search and paper selection process for the meta-analysis.



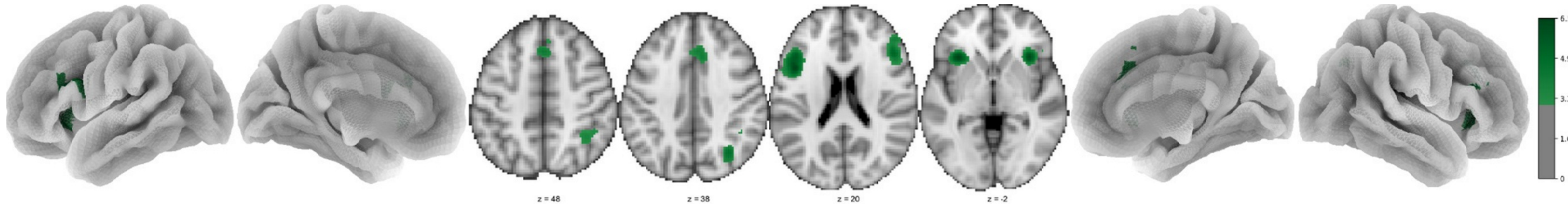


Figure 2. ALE map for pooled (Grammatical + Ungrammatical) results

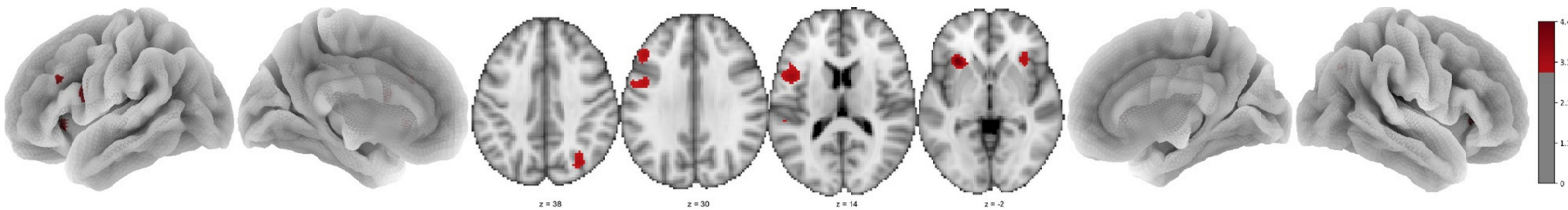


Figure 3. ALE map for Grammatical results

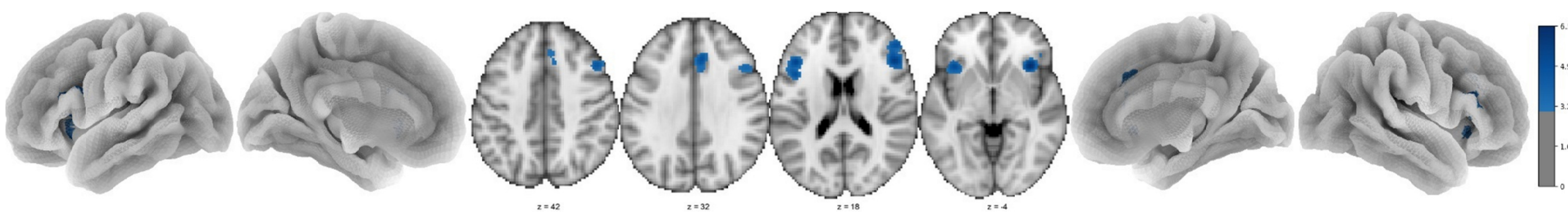


Figure 4. ALE map for Ungrammatical results

Abstract

Implicit learning is the unconscious extraction of rules governing complex stimuli, measured through experiments such as artificial grammar tasks, and is directly related to natural language learning. While several theories address the underlying framework for implicit learning, few studies have shed light on a consensus neural network involved in implicit learning. The short-term goal of this thesis is to further elucidate the brain regions involved in implicit learning of linguistic stimuli. The long-range goal of this research program is to understand how implicit learning and the brain regions associated with it relate to language learning and treatment outcomes in individuals with aphasia. A coordinate-based meta-analysis of 25 studies using implicit language learning tasks was completed. Activation likelihood estimate (ALE) results show significant activation in the bilateral inferior frontal gyri, bilateral insula, left supplemental motor area, right precentral gyrus, right middle cingulate, right middle occipital gyrus, and right inferior parietal lobule. The inferior frontal gyrus is discussed as a general rule-processing and error detection mechanism, and other regional activations are discussed related to their involvement in a cognitive control network. Cognitive control may be seen as an underlying mechanism for successful implicit learning and may be clinically relevant as a target for language intervention to scaffold syntax comprehension.

Elucidating an implicit learning network in healthy adults during artificial grammar tasks

CHAPTER I: INTRODUCTION

Implicit learning is learning that occurs unconsciously and automatically. Implicit knowledge is not explicitly taught, but is stored in long-term memory and retrieved when appropriate, such as the rules underlying language. Implicit learning is a term first coined by Reber (1967) and is defined as the ability to learn the lawfulness of stimulus sequences to efficiently respond to stimuli without explicit knowledge of the rules or explicit strategy use. The ability to implicitly learn has been shown in artificial grammar or serial reaction time tasks in which an increase in accuracy implies that a participant has implicitly learned the underlying rules of the task.

Artificial grammar tasks are composed of two parts: a learning phase and a testing phase. In the learning phase, participants are exposed to stimuli through multiple trials. Stimuli in the learning phase consist of grammatical sentences from which participants will implicitly extract rules about how sentences can be composed. Participants may or may not receive instructions for the task, but rules are never explicitly taught. Following the learning phase, participants enter the testing phase during which they make grammaticality judgments about grammatical and ungrammatical sentences in the artificial language. These sentences consist of grammatical examples heard in the learning phase, random sentences, and sentences that partially follow a rule as a foil. As established by Reber (1967), participants are able to efficiently and accurately judge the grammaticality of sentences created from an artificial grammar while being unaware of the underlying rules or of strategies they may have used.

Serial reaction time tasks are a non-linguistic implicit learning task. In serial reaction time tasks, participants respond to an icon that appears in several locations on a screen. The participants are required to press a button when the icon appears in a new location and reaction time is recorded. The task consists of random and sequenced blocks, during which the icon moves either following a pattern or randomly. Participants begin with a set of random trials, then sequenced trials, followed by another block of random trials. A reduction in reaction time during the sequenced block, followed by an increase in reaction time for the final random block, indicates that the participants implicitly learned the rules underlying the movement of the icon.

While implicit learning is not language-specific, one type of implicit learning called statistical learning, involves hierarchical rule learning which relates directly to language. Statistical learning is the ability to track regularities, or statistical probabilities, in the environment and extract rules from them. Statistical learning is a necessary process for language learning (Saffran, 2001; Saffran, Aslin, & Newport, 1996). While the study of statistical learning of language has focused on infants, adults are also able to listen to unfamiliar languages or artificial grammars and extract regularities, allowing them to make judgements about the grammaticality of an utterance and perform above chance (Bahlmann et al., 2008; Batterink et al., 2015; Lieberman et al., 2004; Petersson et al., 2012; Petersson et al., 2004; Plante et al., 2015; Reber, 1967; Saffran, 2001). What is unique about this type of learning, and implicit learning in general, is that it happens automatically and unconsciously, without specific instructions to learn the grammar or rules.

The ability to implicitly learn is utilized in memory intervention for patients with amnesia in the form of errorless learning. In a meta-analysis by Kessels and de Haan (2003), errorless learning, which utilizes minimization of errors to access the implicit learning system through repetition of correct targets, produced a large effect size of 0.87 across 11 studies. A more recent study by Hart et al. (2020) also found success for errorless learning and minimized reliance on explicit memory in patients with post-traumatic amnesia. However, there are no known language interventions that employ implicit learning strategies and only one experimental study that has used implicit learning treatment with individuals with aphasia. Schuchard et al. (2017) implemented an implicit sentence comprehension treatment utilizing errorless learning strategies with five adults with agrammatic aphasia. The training took place over five sessions, with each session lasting around 20 minutes. Schuchard et al. (2017) found no significant increases in passive sentence comprehension, and three participants showed decreased comprehension scores from baseline. However, the short duration of treatment and difficulty of the task should be noted as they may have prevented treatment gains. Additionally, other studies show that individuals with non-fluent aphasia can perform above chance on serial reaction time tasks involving non-linguistic stimuli, and therefore learn implicitly (Schuchard &Thompson, 2014; Schuchard et al., 2017). Moreover, Christiansen et al. (2010) found that seven individuals with agrammatic aphasia were able to learn an artificial grammar with 91% accuracy during a learning phase, but the average test performance was only 51% when ungrammatical stimuli were introduced, which was not significantly above chance. The ability to implicitly learn has not been examined in other forms of aphasia and has only been minimally tested using artificial grammar tasks to measure implicit learning, thus warranting more research.

In addition to using implicit learning to promote intervention success, the automaticity involved in implicit learning may also assist in generalization of intervention. Generalization requires information to be extracted from stimuli, encoded in memory, and consolidated for automatic retrieval and use. As generalization is the ultimate goal of speech and language intervention, the focus of this study is on the automaticity underlying implicit learning, and specifically statistical learning. One way to better understand implicit learning is by examining the neural correlates of this type of learning and the connections between regions involved in the implicit learning network. Currently, a meta-analysis that clarifies which brain regions are involved in implicit learning does not exist, although two recent meta-analyses have been published examining language learning in adults (Tagarelli et al., 2019) and non-linguistic sequence learning in adults (Janacsek et al., 2020). While Tagarelli et al. (2019) examined artificial grammar learning in adults, their main goal was to look at language learning in general, and not specifically implicit language learning. Additionally, their literature search ended in 2015 and more implicit learning studies have been published since the end of their search. This thesis aims to extend the findings of Tagarelli et al. (2019) by identifying the brain regions involved in implicit learning in healthy adults to serve as a reference for future research.

Model or Framework

One model for the interaction between implicit and explicit learning and their relation to language is the declarative/procedural model (Ullman, 2004). The declarative/procedural model states that the mental lexicon and mental grammar of language are dependent on the distinction between declarative (explicit) and procedural (implicit) memory. The mental lexicon refers to a storage of all “memorized” word-specific knowledge. This includes knowledge of all word meanings and sounds, but also any language unit that cannot be derived from another such as bound morphemes and idiomatic phrases. Conversely, the mental grammar is a computational system that extracts regularities from language, and analyzes language based on knowledge of rules and constraints. The mental grammar is used to comprehend complex forms such as derivational morphology and syntax. The distinction between the two types of language knowledge can also be thought of as explicit versus implicit knowledge of language, as the knowledge contained in the mental grammar is largely unconscious and automatic.

The mental lexicon and mental grammar are served by the declarative and procedural memory systems, respectively. The declarative memory system is responsible for the encoding, storage, and use of semantic and episodic memory for facts and events. This type of memory subserves rapid learning following one stimulus presentation, which binds and associates arbitrarily related information. Declarative memory can also be explicitly recalled. In contrast, the procedural memory system is responsible for learning new skills and controlling established skills, habits, and procedures. Within this system, the knowledge of procedures and the learning of this knowledge is unconscious or implicit. More generally, this system is responsible for the learning and processing of sequences and rule relations in context. Compared to declarative memory, procedural learning occurs gradually and requires several presentations of stimuli. Additionally, the rules are stable, inflexible, not influenced by other systems and are applied rapidly and automatically. These two systems complement each other and work together in the acquisition of knowledge.

That is, when both declarative and procedural systems are intact, they complement each other. However, when one system is impaired, they interact competitively in a “see-saw” effect in which the impaired system leads to the enhanced function of the other system (Ullman, 2004). This is particularly relevant to individuals with aphasia, as the brain damage in one type of aphasia, Broca’s aphasia, is to the inferior frontal gyrus, a structure that Ullman argues is integral to procedural learning. When stating the evidence for the model, Ullman (2004) argues that individuals with non-fluent aphasia have symptoms which may reflect damage to the frontal regions involved in the procedural memory system, while individuals with fluent aphasia show symptoms which may reflect damage to the medial temporal lobe involved in the declarative memory system. Performance-related evidence is listed but no fMRI results are given in Ullman

(2004) to examine the connections between brain regions of procedural memory (i.e., implicit learning) in individuals with aphasia.

The declarative/procedural model describes implicit learning generally but does not provide a framework for how individuals perform hierarchical rule learning, such as statistical learning. One framework for how individuals perform statistical learning is through the use of transitional probabilities, rather than surface level cues of underlying rules. Prior to the framework of transitional probabilities, much of the study of statistical learning focused on discovering word segmentation through surface properties of the stimulus such as frequency of phonemes or presence of unique units. Similarly, artificial grammar learning tasks had focused on tracking surface cues such as frequency of consecutive units (words, syllables, or sounds), frequency of beginning or ending units, lawfulness of the first unit, presence of unique units, location of familiar units, repetition of units, or similarity to previously learned stimuli (Saffran, 2001). However, because natural language is much more complex as phrases are not organized linearly, but hierarchically, it requires more than surface-level cues to extract regularities. Hierarchical organization of phrase structure refers to the organization and grouping of word classes into units (Saffran, 2001). For example, a sentence is made up of a noun phrase and a verb phrase, which can also be broken down into smaller groups and categories of words (e.g., determiners, nouns, verbs).

Saffran (2001) introduced the idea that individuals utilize transitional probabilities to extract phrase structure, or syntax, that are organized hierarchically. These phrases are marked by what Saffran refers to as “dependencies,” meaning a word class requires another specific word class to follow it. For example, determiners such as “a” or “the” must be followed by a noun. However, this does not happen bidirectionally; i.e., a noun does not require a determiner.

Hence, it is not about co-occurrence, but rather the probability of occurrence. Transitional probability refers to the idea that given B, what is the likelihood of A? Or, given a determiner, what is the likelihood that a noun will follow? Saffran (2001) provides support for the use of transitional probabilities by showing that learners can detect phrasal units using predictive dependencies and perform above chance even when all surface level cues are removed such as intonation or stress. The statistical dependencies between the two word classes (e.g. nouns and verbs, or nouns and determiners) are more complex than surface level cues, as they involve hierarchical phrase structure, and provide a framework for the complex rules that can be implicitly learned from natural language.

Traditionally, implicit learning and statistical learning have been separate and distinct research domains (Christiansen, 2019; Perruchet & Pacton, 2006). However, Ullman (2004) provides evidence for the role of implicit learning in the learning/encoding, maintenance, and retrieval of language knowledge. Similarly, Christiansen (2019) coins the term “implicit statistical learning” and argues that the two research domains can be combined as they are both grounded in the basic processes of learning and memory, with an uncontroversial overlap through chunking. Furthermore, Batterink et al. (2015) showed that statistical learning employs implicit learning mechanisms through an implicit reaction time task, so statistical learning may be seen as a type of learning served by the procedural (implicit) memory system. Therefore, this thesis considers statistical learning and implicit learning synonymously.

Neuroimaging Findings

The procedural and declarative memory systems proposed by Ullman (2004) support the mental lexicon and mental grammar language systems via their contribution to learning and through their connections with working memory and attention. In the model, Ullman (2004) identifies several brain regions involved in declarative (explicit) memory and procedural (implicit) memory. Declarative memory utilizes the medial temporal lobe, especially the hippocampus, brain regions around the hippocampus (e.g., the dentate gyrus and subicular complex), the parahippocampal region, the entorhinal cortex, and the perirhinal cortex. Other regions involved include the ventrolateral prefrontal cortex, which is made up of the inferior frontal gyrus, posterior/dorsal inferior frontal cortex, and anterior/ventral inferior frontal cortex. These regions are involved in encoding memory and retrieving declarative knowledge. Additional brain regions involved in retrieval of declarative memory include the anterior frontal-polar cortex and the cerebellum. Further support for the medial temporal lobe's involvement in declarative memory has been established by several papers (Batterink et al., 2019; Gabrielli, 1998; Poldrak et al., 2001).

According to Ullman (2004), procedural (implicit) memory utilizes brain regions similar or related to those for declarative memory. Overall, procedural memory involves a frontal/basal ganglia network, along with the superior temporal lobe, parietal lobe, and cerebellum. Functionally, the basal ganglia are involved in implicit learning in general, but are also implicated in other aspects of implicit learning such as probabilistic rule learning, sequence learning, context-dependent rule selection, working memory maintenance, and attention shifting (Gabrielli, 1998; Poldrak et al., 2001; Ullman, 2004). The dorsal striatum, made up of the caudate nucleus and putamen, is especially important for procedural memory. For example, Plante et al. (2015) found activation in the right caudate was present immediately preceding behaviorally evidenced learning during an unfamiliar grammar learning task. Several implicit learning artificial grammar studies have also found basal ganglia activation, especially in the caudate nucleus (Bahlmann et al., 2008; Forkstam et al., 2006; Lieberman et al., 2004).

Another crucial region for procedural learning is Broca's area, which is responsible for hierarchical sequence learning of linguistic and non-linguistic stimuli (Forkstam et al., 2006; Karuza et al., 2013; Petersson et al., 2012; Ullman, 2004). This region is typically recognized for its involvement in speech and language production, but it may also serve a role more generally in learning and processing sequences. It is also recognized for its role in maintaining information in working memory (Rogalsky et al., 2008). Working memory supports sequence learning by maintaining information to allow for its consideration or manipulation, which may be essential for extraction and computation of underlying rules.

Other regions involved in procedural memory and implicit learning include the superior parietal lobe, inferior parietal lobe, and supramarginal gyrus, likely given their involvement with attention (Corbetta, 2008; Ullman, 2004). Plante et al. (2015) outlines the role of attention in statistical learning and relates their findings of activation in brain regions such as the anterior cingulate cortex and regions in the temporo-parietal-occipital junction to their role in attention. Activation in the anterior cingulate cortex differed between groups, potentially reflecting increased use of attentional strategies by the group who learned more efficiently. In their study, weaker activation in the left parietal lobe, including the angular and supramarginal gyri, was associated with higher rates of correct rejection of ungrammatical utterances. Furthermore, the procedural memory system utilizes the cerebellar hemispheres (the dentate nucleus and the vermis). Functionally, the cerebellum is thought to be involved in error-based learning and error detection, two important aspects of grammaticality judgements in implicit learning tasks (Ullman, 2004).

Need for research

While the declarative/procedural model proposes and provides some evidence for the brain regions involved in implicit learning, there has only been one meta-analysis conducted to test the validity of the proposed frontal/basal ganglia network involved in implicit learning (Tagarelli et al., 2019). Evaluating evidence from a large sample of experiments via meta-analysis may validate the network proposed by Ullman (2004) or provide support for additional regions or a different network of regions that may be involved in implicit learning. This knowledge would benefit future researchers by providing *a priori* hypotheses for studying individuals with an impaired ability to learn implicitly due to stroke or developmental disorders. Subsequent research could then assess whether damage to the implicit learning network impairs an individuals' ability to respond to language intervention and/or generalization of language skills to differing contexts.

Nominal Definitions

Learning: the domain general process of encoding information to support the retention and retrieval of information performed by memory. Learning is evidenced in experiments by an increase in accuracy (Gabrieli, 1998).

Dysfunction/impairment: a decrease in behavioral performance on a task compared to typical healthy subjects or a significant difference in brain function/connectivity associated with less optimal performance.

Statistical/implicit learning: experience-driven learning that occurs by efficiently extracting regularities from input and using probabilities of occurrence to predict future input.

Statistical/implicit learning task: a task or experiment which consists of a learning phase and a testing phase. The learning phase has several trials to promote learning. Explicit instruction or no instruction may be given, but the rules of the stimuli must not be explicitly taught prior to the testing phase. The learning phase involves automatic encoding of rules while the testing phase involves making judgements about stimuli. Accuracy, as measured by performance above chance, is an indication of learning in the task.

Rules: a governing system for stimulus arrangement both within and across units. Target stimuli in implicit learning paradigms are not random and follow a predetermined pattern, set of rules, or grammar as random stimuli are not sufficient for learning. These rules may be linear or hierarchical.

Context

A client's ability to encode, consolidate, and retrieve information is central to their ability to respond to speech and language intervention. A goal of intervention is generalization of language gains, which may be supported by the automaticity that is central to implicit learning. Individuals with aphasia have particular difficulty generalizing language intervention to daily living and continually benefit from intervention many years following their stroke (Marcotte et al., 2012). The motivation for this thesis is that individuals with aphasia have difficulty learning, or making automatic, the implicit rules underlying language. If individuals with aphasia have weaker connections or damage within the implicit learning network, this could change how clinicians provide intervention to strengthen that network, or to bypass it by other means of instruction. The long-range goal is to determine if individuals with aphasia are able to learn language implicitly (Schuchard & Thompson, 2014; Schuchard et al., 2017) or whether the relatively low efficacy of interventions for aphasia may be due to clinicians not providing adequate intervention in terms of dosage, intensity, or time (Kleim & Jones, 2008).

Specific Aims and Hypotheses

The aim of this thesis is to identify a network of brain regions most commonly involved in implicit and/or statistical learning in healthy adults. We hypothesize that, as proposed by Ullman (2004), the basal ganglia, Broca's area, supramarginal gyrus, and superior temporal lobe will be involved. Alternatively, the null hypothesis is that none of these brain regions, other regions, or other networks of regions may be involved in implicit learning.

CHAPTER II: METHOD

Literature search, screening, and paper selection

A comprehensive literature search for peer-reviewed articles was conducted from March 27, 2020 to February 19, 2021. PubMed, PsychInfo, Google Scholar, and references of related articles were systematically searched. Additionally, article data from Tagarelli et al. (2019) provided by Ullman (personal communication, 2020) were searched to determine inclusion eligibility for the current study. See the PRISMA flowchart (**Figure 1**) for the summarized process.

Inclusion Criteria:

- Experimental study
- Participants include healthy adults aged 18 years and older
- fMRI coordinates listed for whole brain analysis
- The task is an implicit learning or statistical learning task (e.g., artificial grammar learning) in any modality
- Contrasts for fMRI are implicit/statistical learning or test > baseline/rest, or a comparison of test stimuli

Search terms used to find relevant articles included: “implicit learning,” “implicit learning AND automaticity,” “implicit learning AND plasticity,” “implicit learning AND fMRI NOT disorder,” “implicit learning AND statistical learning AND MRI,” “artificial grammar,” “artificial grammar AND fMRI,” “statistical learning AND fMRI,” “artificial grammar learning AND fMRI,” “implicit learning grammar AND FMRI,” and “distributional learning AND fMRI.” Searches yielded over 800 papers. Titles and abstracts were then screened by the first author for studies involving language and including brain imaging. The title and abstract screening reduced the total to 228 papers.

Secondary screening was completed by three graduate and three undergraduate students for the following criteria: 1) fMRI or PET studies (not DTI, ERP, or structural imaging) 2) whole brain analysis (not region-of-interest, resting state functional connectivity, dynamic causal modeling, or independent components analysis) and 3) reporting results for healthy adult participants.

Of the 228 papers, 88 were excluded for not utilizing fMRI or PET imaging, or not conducting whole brain analyses. 13 papers were excluded due to not including or reporting results for healthy adults. An additional 32 papers were excluded because they administered serial reaction time task (SRT) experiments that did not involve language.

A final screening was completed for the remaining 150 whole-brain fMRI or PET language studies (95 identified through the literature search and 55 articles from Tagarelli et al., 2019) by the first author to determine whether the study fit inclusion criteria as a study of implicit or statistical language learning. Studies including language learning which referenced rules, grammar, regularities, statistical probability, chunk strength, dependencies, and/or adjacencies were included. These studies either utilized a word learning or a grammar learning paradigm. Studies that focused on word learning were reviewed to determine whether learning occurred implicitly (no translations given), and if there was an underlying rule system. Studies that referenced explicit grammar learning were reviewed to clarify whether rules were explicitly taught (and examine the nature of feedback), and if so, they were excluded. As a result, 36 word learning studies were excluded that either did not involve rules, or explicitly taught words. For the grammar learning studies, one study was excluded (Musso, 2003) and four were retained

(Fletcher, 1999; Skosnik, 2002; Yang, 2012; Yusa, 2011). Finally, studies that explicitly assessed participants' learning of words or grammar, such as recognition and word segmentation tasks, were included since the learning was determined to be implicit.

The final set of 25 fMRI articles were included in the meta-analysis. Twenty-three studies used artificial grammars or languages and two studies used unfamiliar, non-native languages. The types of artificial grammar or languages included BROCANTO (2 papers), Brocanto2 (1 paper), finite-state grammar (10 papers using both Reber and Markovian grammars), transitional probabilities (5 papers), and the remainder included a mix of adjacent, non-adjacent, or pairwise dependencies, hierarchical rules, chunk-based rules, or phrase structure rules (7 papers). Chunk-based rules, also known as associative chunk strength, are a learning mechanism that relies on the frequency of pairs of letters that appear together to make grammaticality judgements (Meulemans & Van der Linden, 1997). See **Table 1** for a summary of papers included in the meta-analysis and a summary of study characteristics.

Meta-data coding for each paper included task definition, stimulus type, stimulus presentation modality, response modality, amount and type of training/learning, feedback type and frequency, and the experimental contrasts. Stimulus presentation mode differed across studies (see **Table 1**) with 15 of the papers presenting visual stimuli and 10 presenting auditory only or auditory + visual stimuli during the learning phase of the experiment. Accuracy feedback (correct/incorrect) was provided in only 8 of the 25 studies, four of which provided feedback during the testing phase as well as the learning phase. However, because feedback only referenced correct/incorrect and was not providing information about specific rules, these eight papers were included.

Contrasts from the coded papers included directional analyses (e.g., group differences or contrast comparisons), increasing activation, decreasing activation, correlation with task performance, and conjunction analyses. Only contrasts reporting (1) increased activation during either a rule-based learning (grammatical) or non-rule-based (ungrammatical) task, or (2) experimental contrasts reporting relevant contrasts between experimental conditions (e.g., rule-based > random) activation in healthy adults were included. Decreasing activations were excluded from the ALE. Additionally, contrasts correlating functional activation during learning with test performance were excluded due to the small number of papers (n=5), thus excluding (Optiz & Friederici, 2004), and leaving 25 papers.

Included grammatical contrasts were those for which activation during a grammatical task (learning or test phase) was contrasted with baseline or rest; or the comparison of activation in grammatical > ungrammatical conditions. A subset of papers (n=12) included greater activation for ungrammatical items, or items that did not follow the learned rules due to violations, than for grammatical items and were included in a separate ALE.

ALE analysis with NiMARE

Coordinate-based meta-analysis (CBMA) was used to identify the brain regions most commonly active during statistical/implicit learning in imaging studies of normal, healthy participants. Following the literature search for previous neuroimaging studies reporting coordinates of brain regions active during tasks that address implicit learning, coordinates identified in the selected papers were analyzed for common patterns of brain activation via an algorithm called the activation likelihood estimate (ALE) (Eickhoff et al., 2012; Eickhoff et al., 2009; Turkeltaub et al., 2012). This algorithm treats the coordinates derived from the selected papers as part of a probability distribution. ALE computes the activation probabilities for each voxel and eliminates random clustering due to noise via a permutation test. The resulting histogram is used to determine p-values for the observed coordinates, which is an indicator of the likelihood of activation at a given voxel. These coordinates are used to generate regions of interest (ROIs) in subsequent analyses. The ALE was run through the Neuroimaging Meta-Analysis Research Environment (NiMARE), a centralized standard implementation of meta-analytic tools through Python (Salo et al., 2020).

Two ALE groups were identified based on the contrasts included: a Grammatical ALE group and an Ungrammatical ALE group. In addition to ALE analyses for each separate ALE group, conjunction, subtraction, and pooled analyses were conducted as well. Conjunction analyses examine the common significant activation, or union between both ALE groups. Pooled analyses included all significant regional activation across both Grammatical and Ungrammatical contrasts. With subtraction analyses in NiMARE, differences between the grammatical and ungrammatical ALE groups were explored across the whole brain, rather than looking for differences in significant activation between the two groups.

CHAPTER III: RESULTS

Results from the Grammatical and Ungrammatical ALE analyses, as well as the conjunction of the two ALEs, are presented in Tables 2 and 3 along with the cluster size, ALE maximum, and anatomical location. **Table 2** shows results for the pooled analysis and **Table 3** shows results for the remaining analyses.

Pooled results for Grammatical + Ungrammatical

As implicit learning involves both the recognition and acceptance of rule-based stimuli and the correct rejection of random, non-rule following stimuli, results from both the Grammatical and Ungrammatical ALE groups were pooled. Pooled analyses indicated six clusters of activation: 1) the left inferior frontal gyrus, specifically the pars opercularis, extending to the left insula, 2) the right inferior frontal gyrus, specifically the pars triangularis, extending to the right precentral gyrus, 3) the right middle cingulate gyrus extending to the left supplemental motor area, 4) the right insula, 5) the right middle occipital gyrus, and 6) the right inferior parietal lobule.

Grammatical ALE results

Five clusters comprised of seven regions across both hemispheres were significantly active across subject groups, z-corrected FWE thresholded at $p < 0.05$. The clusters included: 1) the left inferior frontal gyrus, extending from the precentral gyrus to the pars triangularis, 2) the left insula, 3) the right middle occipital gyrus, 4) the right insula, and 5) the left superior temporal gyrus.

Ungrammatical ALE results

Four clusters comprised of eight regions showed significant activation across subject groups, z-corrected FWE thresholded at $p < 0.05$. The four clusters were located in both the left and right hemispheres. The clusters included: 1) the left inferior frontal gyrus, specifically the pars opercularis, extending to the left insula, 2) the right middle frontal gyrus extending to the right inferior frontal gyrus, specifically the pars orbitalis, 3) the right middle cingulate gyrus extending to the left supplemental motor areas, and 4) the right insula.

Conjunction analysis results

The union of the Grammatical and Ungrammatical ALE groups showed three regions of convergence, organized in two main clusters: 1) the left inferior frontal gyrus, including the pars opercularis and triangularis and 2) the left insula.

Subtraction analyses

Subtraction analyses were also performed. However, subtraction analyses did not yield any significant results for $p\text{-FDR} < 0.05$.

CHAPTER IV: DISCUSSION

In this coordinate-based meta-analysis, we examined the neural correlates of implicit learning in healthy adults during language learning tasks. To examine this, we conducted several ALE analyses of previous artificial language learning studies and pooled the results to determine a network of regions involved in implicit language learning. The aim of this CBMA was to elucidate which brain regions are involved in implicit learning as this process is central to natural language learning and may be applied clinically to understand more about how individuals with brain differences optimally respond to language intervention. As a result, we found a network of bilateral activation, primarily in the bilateral inferior frontal gyrus and bilateral insula, as well as activation in the right precentral gyrus, right middle cingulate, left supplemental motor area, right middle occipital gyrus, and right inferior parietal lobule.

The pooled results of both the Grammatical and Ungrammatical ALE analyses included some brain regions that were hypothesized to be active, such as the left IFG, and others that were not, such as the bilateral insula. The pooled results, rather than the conjunction of the two ALEs, was chosen as the main analysis over analyzing the ALE groups separately as both the ability to correctly identify rule-following input and accurately reject rule violations are equally important in acquisition and use of implicit rule-learning which is essential to language. In the following sections, we will discuss the implications of the results observed.

Subtraction results were completed to determine if there were statistically significant differences in activation between the Grammatical and Ungrammatical ALE groups. However, there were no significant results, which shows that grammatical and ungrammatical stimuli do not engage functionally different regions, or that there was not enough power to detect significant differences. Nonetheless, some differences were present, with more left-lateralized activation for the Grammatical ALE as well as left superior temporal gyrus activation for the Grammatical ALE (as predicted by Ullman, 2004). In the Ungrammatical ALE, some differences included right IFG involvement, as well as activation in the middle cingulate and supplemental motor area. The lack of significant differences between the two ALE groups is not surprising. Several studies found no significant activation for contrasts examining differences between grammatical and ungrammatical activation (Folia & Peterrson, 2014; Hauser, 2012).

Inferior frontal gyrus

The inferior frontal gyrus was the most consistently active region in all analyses, including the Grammatical, Ungrammatical, conjunction, and pooled ALE analyses. Specifically, the left pars opercularis was the part of the IFG that had the strongest activation across all 25 studies. This finding was not surprising, due to its role in processing syntax (Bookheimer, 2002; Friederici, 2018; Peterrson et al., 2012) and its hypothesized role in Ullman's (2004) declarative-procedural model. Several studies have reported that the left IFG plays a more general role in rule processing (Forkstam et al., 2006; Karuza et al., 2013; Peterrson et al., 2012). Following the results of an implicit word segmentation task involving forward and rule-violating backward speech, Karuza et al. (2013) posited that the left IFG functions as a mechanism that directs sequence learning by computing statistical regularities and forming structural representations. Forkstam et al. (2006) found that the left IFG (BA 45) was sensitive to grammaticality and not the level of associative chunk strength, showing that it plays a "specific role in processing structural regularities" (p. 964). On the contrary, Forkstam et al. (2006) found that the right IFG was more sensitive to associative chunk strength, which may reflect general error detection processes. Taken together, Forkstam et al. (2006) suggests that the left IFG is involved in processing the structural aspects of mental representations and may provide a "neural infrastructure for structural integration" (p. 964). This finding supports the results of this CBMA, mainly that the Gramamtical ALE only found left IFG activation, whereas the Ungrammatical ALE, which involves more error detection, revealed bilateral IFG involvement.

The peak coordinates found for the pars opercularis differed across ALE analyses, which may be important as there has been some evidence of functionally different roles within the frontal operculum. In a study examining native language syntax processing, Friederici et al. (2006) found functionally distinct portions of the pars opercularis for grammaticality and complexity. Specifically, they found that the inferior portion of the pars opercularis of the left IFG was more sensitive to complexity than grammaticality (referred to as the BA 44i, x = –49, y = 10, z = 4) and that the posterior portion of the left frontal operculum (2 cm posterior to 44i) was more active for ungrammatical sentences than for simple and complex grammatical sentences (referred to as pFO, x = –46, y = –7, z = 17). This finding may explain why different coordinates were found for the Grammatical and Ungrammatical ALE analyses. Further analyses could be completed to examine this further.

Additional differentiation among the left and right inferior frontal gyrus was shown by Bahlmann et al. (2008). In their artificial grammar study, Bahlmann et al. (2008) found more left IFG activation for hierarchical rules rather than adjacent rules for both grammatical and ungrammatical stimuli. This peak was within the posterior portion of the pars opercularis, with the majority of activation within the middle of the pars opercularis. This finding contradicts the results of Friederici et al. (2006), that complexity is processed in the inferior portion of the left pars opercularis. However, when examining hierarchical compared to adjacent rules for both the grammatical and ungrammatical stimuli, only the grammatical stimuli showed activation in

Broca's area. This finding that grammaticality engages the left IFG and not the right IFG is consistent with the current findings as well as those of Forkstam et al. (2006).

Through functional connectivity analyses, Yang and Li (2012) found that the inferior frontal gyrus was a "hub of neural activities, exerting strong top-down influences on other nodes" (p. 5) with connections to both the insula and the caudate. The current CBMA has found significant importance for this structure as well, as the IFG was the most consistently active structure in all ALE analyses. Additionally, the left IFG was shown to be significantly correlated with implicit learning test performance in studies by Morgan-Short et al. (2015) and Finn et al. (2013).

In summary, the inferior frontal gyrus is an important region for grammaticality or rule processing, complexity of rules (i.e. adjacent or non-adjacent), and detection of errors. This region is active bilaterally, and there may be functional differentiation between the two hemispheres for grammaticality and error detection. Furthermore, there may also be further differentiation within the left pars opercularis for grammaticality and complexity.

Insula

The left and right insula were found to be active consistently across all studies, with more extensive activation in the left insula. The insula has been found to be involved in language processing, cognitive control, and as an active region in the salience network (Corbetta et al., 2008; de Diego-Balaguer et al., 2016; Jiang et al., 2015; Menon & Uddin, 2010; Oh et al., 2014). In studies of artificial grammar, the insula seems to play a role not directly related to the nature of the stimuli, but as an important part of maintaining attention to the task. In an artificial grammar study, Bahlmann (2008) found activation in the insula for all contrasts, regardless of rule type (hierarchical vs adjacent rules), length (short vs long sequences), and grammaticality, which suggests that it is not specific to hierarchical rule processing and may be more indicative of the mental effort of the task. Yang and Li (2012) showed that the insula was important for explicit learning compared to implicit learning, where explicit meant that the participants were informed that the stimuli were governed by rules but not taught what the rules were. Therefore, the insula could be important for goal-directed conscious evaluation of stimuli. Moreover, Yang and Li (2012) found connections between the IFG and insula for implicit learning, with bidirectional connections between the insula and the caudate. They hypothesized that the insula acts as a mediator between the IFG and the caudate in the more explicit learning task where participants were informed about the presence of rules, which points to higher level intentional processing. Additionally, Deschamps et al. (2016) found greater cortical thickness in the anterior insula which they associated with higher sensitivity to statistical structure. They hypothesized that increased cortical thickness is related to better ability to focus attention and therefore results in better detection of statistical regularities. Given the insula's role in the salience network and cognitive control, it is not surprising that artificial grammar tasks, which require tracking regularities across complex stimuli, engage the insula. Consistent involvement of the insula across all ALE analyses may highlight the role of attention and cognitive control in implicit language learning. Further research could be done to determine the predictive weight of language ability versus cognitive control in implicit learning performance.

Other activations

Other significant activations included the right precentral gyrus, right middle cingulate gyrus, left supplementary motor area, right middle occipital gyrus, and right inferior parietal lobule. The right middle cingulate gyrus was significantly active in the Ungrammatical and the pooled ALE analyses. The anterior cingulate is well known to be involved in cognitive control, and a coordinate-based meta-analysis found that the cingulate is active for inhibition, flexibility, and working memory tasks across 193 studies (Niendam et al., 2012). While the current CBMA found significant activation in the middle cingulate, the activation was located very close to the border of the anterior cingulate gyrus. In a study examining adjacent and non-adjacent dependencies, Conway et al. (2020) contributed cingulate activation in the non-adjacent rule condition to more difficult cognitive processing due to the need to inhibit intervening items in order to extract the non-adjacent paired stimuli. Similar to the cingulate, the precentral gyrus has been found to be involved in cognitive control, and has been implicated in inhibition, flexibility, and working memory tasks (Niendam et al., 2012). Additional results from Niendam et al. (2012) implicate the right inferior parietal lobule in these tasks as well. The supplementary motor area (SMA) has been traditionally thought of as being involved in motor control, but it has also been implicated in verbal working memory, as an interface between procedural and declarative memory, and the pre-SMA has been found to be involved in cognitive control, especially for complex sequencing, task switching, and ambiguity resolution (Hertrich et al., 2016).

Given the large number of studies (20/25) that utilized visual stimuli, it is not surprising that we found significant activation in the occipital lobe in the pooled ALE results. In addition to visual perceptual processing accounting for occipital activation, Conway et al. (2020) posited that the occipital cortex may be recruited for “improved processing and perceptual facilitation of encountered stimuli in a modality-specific manner” (p. 11). This follows from the Reber (2013) theory that implicit learning occurs through the distributed representation of information which is gradually accumulated over several repetitions.

There were some expected activations that we did not find, such as that of the basal ganglia due to its hypothesized role in the frontal basal network of the declarative-procedural model (Ullman, 2004). This could be due to a variety of reasons. One potential reason is that basal ganglia activation is not present for the duration of learning. Plante et al. (2015) found right caudate activation during a non-native language learning task only at the onset of measurable learning. Similarly, Forkstam et al. (2006) found that the caudate was originally sensitive to associative chunk strength on day one of their study but became sensitive to grammatical items and not chunk strength on day eight. Folia and Petersson (2014) also found basal ganglia activation, but this effect was stronger on day five than day one. These studies provide some evidence that the basal ganglia are important for implicit learning, but that this structure may not be consistently involved throughout the process. Another potential reason that we did not find basal ganglia activation is that ALEs do not examine deactivation contrasts.

Potential frameworks for understanding implicit learning

The results of this meta-analysis did not fully support the declarative-procedural model from Ullman (2004) as no significant activation was found in the basal ganglia. This may be due to the heterogeneity of studies, contrasts, or due to the limited number of studies included. The results indicate some regions well known to be involved in language, such as the left inferior frontal gyrus, but mainly show bilateral distributed activation of regions which includes regions involved in the cognitive control network such as the insula, cingulate, and precentral gyrus (Niendam et al., 2012). These results may support a cognitive control framework as a scaffold for rule identification, maintenance, and decision making.

Another brain network relevant to implicit learning is the frontoparietal network. Attention is an important factor in any task, and the ability to attend to and track regularities across artificial grammar stimuli is imperative for rule identification and application. In a non-native language learning task, Plante et al. (2015) found consistent activation in left anterior cingulate cortex across all high predictability scans and concluded that this may reflect the use of an attentional strategy to extract word forms. Indeed, several studies have stressed the importance of attention and cognitive control in the ability to track regularities (Conway et al., 2020; Ordin et al., 2020; Yang & Li, 2012). A twofold model by Corbetta (2008) details two interrelated networks: the dorsal and ventral frontoparietal networks. The dorsal frontoparietal network is involved in goal-directed attention and includes regions such as superior parietal lobe and middle prefrontal cortex, including the precentral sulcus. It is also involved in connecting relevant stimuli to responses. On the contrary, the ventral frontoparietal network engages several regions involved in implicit learning such as the inferior parietal cortex, middle frontal gyrus, inferior frontal gyrus, frontal operculum, and anterior insula (Corbetta, 2008). This network is involved in stimulus-driven attention for relevant stimuli. This attention network encompasses most of the regions found in this CBMA. Stimulus-driven attention is relevant to implicit learning, as this form of attention cues individuals into the relevant attributes of the signal, which allows for extraction of the underlying rules central to implicit learning. Similarly, de Diego-Balaguer et al. (2016) highlights the role of temporal attention as a scaffold for language development.

An alternative explanation is provided by Reber (2013), who suggests that there is not one single neural network for implicit learning, rather implicit learning arises through a distributed representation of information across the whole brain. According to this theory, information is accumulated over time through repetitions, and is processed throughout the cortex to maximize learning. While this theory does not help pinpoint which regions are most important for implicit learning, it may explain why among the five studies correlating test performance with fMRI activation during learning did not have a consensus of regions that are correlated with accuracy during implicit learning tasks (Finn et al., 2013; Hauser et al., 2012; Karuza et al., 2016; McNealy et al., 2006; Morgan-Short et al., 2015; Opitz & Friederici, 2004).

Taking these theories together, attentional mechanisms may be used to cue individuals into the relevant regularities in the signal, and cognitive control may be employed to inhibit superfluous information in the signal and maintain/update representations to support learning.

Significance as it relates to aphasia

The ability to statistically learn is essential to language acquisition, and the automaticity involved in implicit learning is likely relevant to successful language intervention. Individuals with aphasia have difficulty generalizing treatment targets and would benefit from a strategy to make language more automatic (Marcotte et al., 2012). Implicit learning may be a skill that could support individuals with aphasia during language treatment through making the rules of language, specifically syntax, more automatic. The results of this coordinate-based meta-analysis suggest that the ability to implicitly learn may not be determined by language ability, but rather may be subserved by the cognitive control network as shown by activation in the insula, cingulate gyrus, precentral gyrus, SMA, and inferior parietal lobule. Cognitive control mechanisms may aid in maintaining and updating the incoming signal (e.g., words and sentences produced by a conversational partner) while also inhibiting unnecessary information. This network may be strengthened in individuals with aphasia through tasks targeting executive functions or working memory in order to boost language performance. The ability to inhibit unnecessary input while also maintaining relevant information and updating this representation across time is important for successful communication.

Individuals with aphasia have been found to perform above chance on non-linguistic serial reaction time tasks (Schuchard &Thompson, 2014; Schuchard et al., 2017). However, their ability to perform linguistic implicit learning tasks has not been widely tested. Christiansen et al. (2010) found that individuals with lesions in the left IFG were able to learn an artificial grammar with high accuracy, but the average test performance was only 51%, which was not significantly above chance. The difference between the individuals with aphasia and the healthy controls was in correct endorsements and not correct rejections, which Christiansen et al. (2010) determined to show a deficit in implicit learning rather than in language ability. If individuals with aphasia were trained to be more successful implicit learners, the ability to calculate the statistical probability of incoming information (i.e., predicted word class) may reduce processing load. A common intervention strategy is to reduce a speaker's sentence length when speaking with an individual with aphasia. Strengthening the implicit learning network may allow for increased syntax comprehension, and reduced processing load due to ability to infer incoming information. This may aid in an individual with aphasia's ability to comprehend longer and more complex utterances.

The left inferior frontal gyrus was the brain region showing the most activation during implicit learning tasks, and this region is often the site of lesions in individuals with aphasia. However, the inferior frontal gyrus was found to be active in both hemispheres during implicit learning tasks, as well as activation in the insula and other regions. This bilateral activation in the IFG is promising since individuals with aphasia could recruit the right IFG for implicit learning and potentially still be successful. If these individuals were trained to rely more on domain general executive functions and working memory, the left IFG may be able to be bypassed. Individuals could potentially benefit from implicit learning training to make language processing more automatic and aid in syntax comprehension. More research is needed in the future to determine the clinically utility of training this skill.

Limitations

This coordinate-based meta-analysis had several limitations. First, there were only a small number of studies included (25), due to the limited number of artificial grammar studies that used both fMRI and analyzed whole brain results. Second, this study was interested in language specifically, so serial non-linguistic reaction time (SRT) tasks were excluded. However, by excluding SRT tasks, we are unable to determine whether the brain regions involved in implicit language learning are similar or different from the brain regions involved in implicit learning of any stimuli. Moreover, we were unable to comment on whether left inferior frontal gyrus involvement is due to the linguistic nature of the tasks included, or if it plays a role as a domain general rule-processing mechanism as other studies have proposed (Forkstam et al., 2006; Karuza et al., 2013; Petersson et al., 2012).

Regarding the studies that were included in the CBMA, there was a lack of consistency among the studies in terms of which phase of the experiment the participants completed fMRI scanning, which contrasts were analyzed, the inclusion of a baseline task, inclusion of feedback, the different types of rules (i.e., hierarchical vs linear) learned, modality of the stimulus, and length of the experiment (number of trials, how long trials were, and across number of days). As seen in Table 1, four studies completed scanning during the learning phase, 16 completed scanning during the testing phase, and five studies scanned participants during both phases, thus examining the activation during the learning process and the use of learned information to make decisions regarding the grammaticality or rule-based nature of stimuli. Additionally, eight studies provided some form of feedback, such as indicating whether a response was correct/incorrect or having individuals hand copy grammatical strings three times if they produced them incorrectly. Feedback was received mostly during the learning phase, but three studies gave feedback during the testing phase. While feedback generally violates the implicit nature of learning, these studies were included due to the limited number of studies that met criteria and because no information about the rules were taught, thus the underlying rules remained implicit. However, providing feedback to learners makes the learning process active rather than passive, which may aid learning (Tricomi & DePasque, 2016). As some studies employed hand copying grammatical strings as practice to promote rule extraction, this could provide an extra boost for kinesthetic learners and skew results for brain regions involved in individuals who are good learners. Similarly, only one study (Goranskaya et al., 2016) examined the effects of learners versus non-learners, which would be clinically useful to determine which regions good learners employ and which brain regions need to be targeted in therapy to boost extraction skills. Lastly, most studies included visual presentation of language stimuli, which is not how language is learned naturalistically. Additionally, not all studies included hierarchical rules, which is how natural language is organized (Saffran, 2001). Future coordinate-based meta-analyses analyzing implicit learning may benefit by including studies that are more similar to each other as well as finding studies that examine learning over several days to assess early and more stable, consolidated learning.

Future directions

Results from this coordinate-based meta-analysis can be followed by several different analyses to further elucidate whether the regions found to be active in implicit learning comprise a connected network. Using the human connectome project data, resting state functional connectivity between the IFG, insula, and other regions of interest found in this study may be examined in the healthy adult data to determine whether the regions are functionally connected and if so, the strength of these connections. Additionally, meta-analytic connectivity maps

(MACM) can be calculated. Functional decoding may also be completed, analyzing the data provided in Neurosynth, an open-science repository of brain imaging studies, to determine what tasks typically activate the regions of interest found in this CBMA.

Further research can also shed light on the clinical relevance of these findings. In the future, we plan to examine whether these regions of interest are connected in resting state fMRI scans of individuals who have sustained a stroke and have resulting aphasia. More studies looking at implicit learning in individuals with aphasia are also needed, specifically studies comparing linguistic and non-linguistic implicit learning ability in these individuals. Performance may then be correlated with treatment outcomes, to determine whether the ability to learn implicitly is an important skill for treatment and/or generalization of treatment, given the connection to the implicit statistical nature of natural language.

Regarding future directions to examine implicit learning, more research on what defines a “successful” implicit learner is needed. Results from this study indicate a strong involvement of executive functioning skills and recoupment of regions involved in cognitive control. More research on which brain regions are active in early, middle, and late stage learning as well as consolidation and generalization of implicit learning would allow researchers to further understand which brain regions are active during specific time points in learning and which may be active throughout. A study by Plante et al. (2015) found that brief caudate activation signaled the beginning of successful behavioral performance, and more research on neural activation across the learning process may provide more support for basal ganglia involvement in implicit learning. Additionally, more studies correlating activation during learning and behavioral performance on implicit learning tests are needed. A third ALE group including these contrasts was considered, but there were only five studies including contrasts examining this connection in learners and therefore the ALE could not be completed. Implicit learning is a growing field of research with many applications to clinical populations. Additional research on this ability will benefit how we provide treatment and optimize treatment outcomes.

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