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Neurophysiological Mechanisms of Statistical Learning in Adults with and without Reading Disorders

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NEUROPHYSIOLOGICAL MECHANISMS OF STATISTICAL LEARNING IN ADULTS WITH AND WITHOUT READING DISORDERS

by

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Under the Direction of Christopher M. Conway, PhD and David Washburn, PhD

ABSTRACT

The artificial grammar learning (AGL) task first introduced by Reber (1967) as well as similar paradigms (e.g., Jost et al., 2015) are thought to elicit implicit statistical learning (SL) of underlying patterns in typical readers. However, previous research has shown that individuals with dyslexia often show difficulty with such incidental learning, on AGL and other SL tasks (Kahta & Schiff., 2016; Singh, Walk and Conway, 2018). Because few studies have investigated this link between statistical learning and reading ability, the current study was designed to examine the neurophysiological and behavioral correlates in adults with and without a reading disorder diagnosis. Sixteen reading impaired and thirty-seven typically reading adults were recruited for the study and completed the AGL, and SL (visual-motor; auditory-motor) tasks, followed by completion of questionnaires eliciting awareness of underlying patterns. During these tasks, behavioral measures such as response times and grammaticality classifications were recorded. Additionally, event-related potentials (ERPs) were also acquired during the computerized tasks. Following this, normed assessments indexing cognitive, reading and spelling ability as well as basic musical ability were administered to participants. Prevalence of attention-deficit symptoms was also accounted for by administration of a checklist. The aim was to assess the underlying mechanisms of implicit-statistical learning such as *transition-timing* and *chunking* as well as *grammaticality* (algebraic patterns and ordinal knowledge) via varied task paradigms (SL and AGL respectively) and non-linguistic stimuli. Although behavioral results were comparable across groups, ERP amplitude differences vary in topology across groups – especially for grammaticality and chunk strength, but not so much for the transition timing paradigms. For atypical readers, correlations were only found between symbol search scores and ERP responses for grammaticality. Thus, overall, the current study highlights the need to assess participants in terms of overall learning capacity before investigating the link between implicit-statistical learning capacity and reading ability. Additionally, findings indicate that participants were not as sensitive to non-linguistic items across learning paradigms as they might have been to purely linguistic items.

INDEX WORDS: Dyslexia, Reading Ability, Implicit Learning, Statistical Learning, Event Related Potentials

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LIST OF ABBREVIATIONS

AGL	Artificial grammar learning
ADHD	Attention deficit hyperactivity disorder
CNz	Medial central
DSM-5	Diagnostic and statistical manual of mental disorders, 5th edition
EEG	Electroencephalography
EGI	Electrical Geodesic Inc.
ERP	Event related potentials
FRz	Middle anterior
ISL	Implicit statistical learning
μV	micro volts
ms	Milliseconds
LAn	Left anterior
LCn	Middle central
LP	Low predictability/ predictor
LPo	Left posterior
OMSI	Ollen Musial Sophistication Index
POz	Middle posterior
RAn	Right anterior
RCn	Right central
RCLD	Regents center for learning disorders
ROI	Region of interest
RPo	Right posterior

RT	Response times
SL	Statistical learning
SLD	Specific learning disorder
SRT	Serial reaction time
ZP	Zero predictability/ predictor

1 INTRODUCTION

1.1 Statistical Learning

We spend a good portion of our daily lives engaged in learning patterns that we discover in our immediate surroundings; sometimes this occurs so unconsciously we don't even realize it until asked to report a sequence or pattern. For instance, when learning the rules of grammar in an unfamiliar language one may rely on implicit patterns between words and syllables that only become obvious over time. By virtue of exposure, the human brain picks up on sequences by capitalizing on repetitions, as in, a catchy tune frequently played on the radio. Another example is learning to play a musical instrument, in which certain motor sequences must be carried out to produce specific musical notes that ultimately result in a desired tune. In music, most of these non-random sequences follow musical regularities that must be learned by the beginner. In this way, our environment is teeming with occurrences involving learning of statistical contingencies and non-random sequences; this learning often become automatic.

There are two related research literatures that have focused on studying this phenomenon, namely statistical learning and implicit learning. Statistical learning refers to the ability to learn statistically structured patterns from the environment and is often considered to occur without explicit awareness of the underlying patterns (Perruchet & Pacton, 2006), although some amount of awareness appears to accompany learning in certain tasks (Singh, Daltrozzo & Conway, 2017). Statistical learning occurs when the observer is able to extract statistical probabilities from input (Saffran, Newport & Aslin, 1996) under incidental learning conditions. Such a high sensitivity to structure can also be seen as a prerequisite for language acquisition in general (Romberg & Saffran, 2010) and for syntactic processing in particular (Kidd, 2012). Implicit learning as defined by Reber (1967) refers to the individual ability to express acquired knowledge through task performance without awareness for such information. Implicit learning is manifested through experience with the environment via repeated encounters with stimuli and also by extracting statistical structure (i.e. categories, sequences) from the environment (Reber, 2013). Because of the implicit nature that is typical of statistical learning, the line between statistical learning and implicit learning is sometimes unclear.

Research on statistical learning ability has extended to include its impact on other cognitive processes such as reading ability (Folia et al., 2008; Gabay, Thiessen & Holt, 2015). Dyslexia - a common learning disability that specifically impairs a person's ability to read – affects roughly 3% -7% of the population (Peterson & Pennington, 2012). Common characteristics among people with dyslexia are difficulty with phonological processing (the manipulation of sounds) and spelling (Gabrieli, 2009). Individuals with dyslexia show comorbidity with attention deficit hyperactivity disorder (ADHD), auditory processing disorder and in general, have trouble with learning (Fawcett & Nicolson, 2007; Habib, 2000).

To explore the link between implicit-statistical ability and reading impairment further, the current project aims to investigate the neural and behavioral correlates of statistical learning associated with: (1) chunking (2) grammaticality and (3) predictability. The naming conventions surrounding these three learning variables has arisen from the literature and this is explained ahead, in line with information-extraction mechanisms outlined by Dehaene, Meyniel, Wacongne, Wang and Pallier (2015). The aim of the current study is to examine the acquisition of information captured by these variables in adults both with and without reading disorders. Before addressing the details of the current study, a brief overview of statistical learning and implicit learning research, followed by the types of information acquired via such learning, and the similarity of these two learning approaches are presented below. This is then followed by a chapter on reading disability theories along with relevant findings related to implicit/statistical learning and reading ability.

1.2 Overview of implicit learning and statistical learning research

Implicit learning research originated with Reber's (1967) studies using the artificial grammar learning paradigm. Artificial grammar learning is an established tool used to probe implicit learning abilities (Dienes, Broadbent, & Berry, 1991; Reber, 1967); more specifically it was used to investigate whether people could learn the grammatical patterns (order of letters) presented within letter strings simply by exposure to those stimuli. A typical artificial grammar learning task comprises of a familiarization phase involving exposure to sequences generated from an artificial grammar. Next, participants are presented with the test phase in which they are prompted to classify novel sequences as grammatical or not. Artificial grammar learning performance is sometimes measured in terms of two types of information that participants might learn, namely, 'grammaticality' and 'chunk strength' (Knowlton & Squire, 1996). Grammaticality is the extent to which the training stimuli comply with the finite state grammar employed. Chunk strength refers to whether a test item is composed of previously encountered parts in the training phase; it also generally corresponds to similarity with items.

Besides the artificial grammar learning task, a serial reaction time (SRT) task has also frequently been used to measure implicit learning (Nissen & Bullemer, 1987; Robertson, 2007). In this task the participant is repeatedly presented with stimuli which contain cues as to what response is to be made (button press). The participant is not informed about the structure underlying cue transition and that each cue follows another with some degree of predictability (repeated sequences). When participants learn these transitional probabilities, their response times

(RTs) decrease. This reduction in RTs is not just due to familiarity with the task or other practice effects; it is specific to the sequence /transitional probabilities that participants have learned.

Landmark studies in the field of statistical learning began with Saffran et al., (1996). In this study researchers demonstrated that when 8-month old infants were exposed to an artificial language (with nonsense words) presented as continuous speech, they were capable of using sequential statistics to extract information regarding word boundaries. The first part of the study involved familiarizing infants to two minutes of the speech stream (example: 'bidakupadotigolabubidaku'). Statistical learning was then assessed by a test phase in which the infants were presented with words from the familiarization phase in addition to new non-words that were created with the same syllabic structure as in the familiarization phase but in a different order than before. Infants indicated learning by displaying a longer listening time for non-words compared to words. Since this first study contained frequently occurring syllables a second study was created (Saffran, 1996), using a more complex structure involving relatively lower transitional probabilities capable of alerting the listener to word boundaries. For instance, in the example, 'pretty#baby' they wanted to investigate whether infants could break down word-internal syllabic structure from the external structure such as 'ty#ba'. This second experiment was similar to the first, except now during test, infants heard both words and part-words created by combining a final word syllable to the first two syllables of another word. These could only be detected as novel if infants' learning during familiarization was already robust enough to discriminate against those that crossed the word boundary. Infants did indicate an ability to discriminate between word and part-word stimuli with longer listening times for part-words. This statistical learning phenomenon has been replicated across children (Saffran et al., 1996; Vicari, Marotta, Menghini, Molinari &

Petrosini, 2003) and adults (Bennett, Romano, Howard & Howard, 2008; Du & Kelly, 2013) across visual (Fiser & Aslin, 2002) and auditory (Saffran et al., 1996) modalities.

1.2.1 ***Types of information acquired in statistical learning***

Although statistical learning and implicit learning have some obvious similarities, it could be that they are manifested (behaviorally and neurally) in different ways and might be associated with extraction of different types of information during learning. One type of information involved in statistical learning is probabilistic prediction-based learning or 'transition-timing' based and this term is referred to later in this section. Recent published studies using a probabilistic learning task, such as Daltrozzo et al., (2017) incorporated stimuli that were ascribed to a high, low or zero 'predictability' (HP, LP, ZP, respectively) condition. This meant that in each of those conditions the probability of a target following a predictor stimulus was 90%, 20% or 0%. Participants' reaction times exhibited quicker responses to the target when it was preceded by the HP compared to the LP condition, demonstrating learning of the predictor-target contingencies (Daltrozzo et al., 2017; Jost, Conway, Purdy, Walk & Hendricks, 2015). Participants also exhibited a neural profile that distinguished the HP from the LP (i.e. there was a larger P300-like effect or positive centro-parietal amplitude for the HP compared to the LP). An important feature of this task is that it is used to measure transition-timing / prediction-based learning (using RTs and ERPs). Additionally, in the case of this task, the ERPs are the best measure of prediction-based learning as learning is elicited based on the predictor, before the target occurs.

On the other hand, in the artificial grammar learning task, participants are thought to acquire information and learn via chunking or fragment-based learning as well as pattern learning or learning to extract regularities dictated by the grammar. These information types are further broken down as per learning mechanisms described by Dehaene et al. (2015) and are discussed later. It is important to note that learning in an artificial grammar learning paradigm has an additional layer of complexity in that, to perform efficiently, a participant must not only be able to learn grammar and chunk strength information but must also be able to consolidate that knowledge and successfully reapply it to new sequences, which is not the case in most other statistical learning or predictability-based learning paradigms.

In Knowlton and Squire's (1996) artificial grammar learning study a balanced chunk strength design was used. Associative chunk strength (average of individual item chunk strength) was defined by the chunk or bigram/trigram frequency during training. Grammatical and nongrammatical items contained an equal number of high and low chunk strength items. Thus, the balanced chunk strength design is important because the degree to which test items follow grammatical structure is balanced with the frequency of sequence appearance (bigrams and trigrams) in the training item set. This was done to avoid the underlying grammatical structure at test being confounded by exposure to individual chunk frequency at training. Test phase items can be created to conform to four types of items: (i) grammatical and high chunk strength; (ii) grammatical and low chunk strength; (iii) nongrammatical and high chunk strength and (iv) nongrammatical and low chunk strength. Grammatical items follow the grammar as opposed to the nongrammatical ones, which contain grammatical errors.

In their study, Knowlton and Squire (1996) were interested in determining the influence of grammaticality and chunk strength knowledge on artificial grammar learning in amnesic patients vs. controls because amnesia has been linked to impaired declarative memory but intact non-declarative memory (Squire, 1992). Thus, if their learning was intact then that would mean that declarative memory systems (medial temporal lobe/ hippocampus) were not integral to AGL. In Experiment 1, test items were constructed so that grammaticality (overall rules) were balanced (unconfounded) with item frequency (between test items and training sets). This was done to examine whether grammaticality judgement was independently influenced by grammaticality and chunk strength. Findings form Experiment 1, indicated that both compliance with grammatical rules and chunk strength had similar influence on grammaticality judgment, in amnesiacs and controls. Despite controlling for chunk strength, both groups endorsed grammatical test items more than nongrammatical items. Additionally, an item's chunk strength separately influenced the tendency to endorse the item as grammatical or not, specifically observed only for nongrammatical items. Such findings support the notion that rule-based information influences classification judgments and the influence of exemplar-specific information is an additional contribution. Experiment 2, involved examining whether amnesic patients acquired sufficient knowledge about chunk strength to account for their intact grammatical classification ability. In contrast to experiment 1, findings from experiment 2 revealed that amnesic patients' recognition memory for letter chunks was severely impaired, indicating that successful classification performance by amnesic patients cannot be accounted for by their declarative knowledge about grammatically allowable chunks. This indicated that although their grammaticality knowledge was mediated by declarative memory, chunk strength knowledge (implicit) was associated with non-declarative systems. In Experiment 3, Knowlton and Squire (1996) examined the degree to which grammatical knowledge was abstract by investigating the ability of (controls and amnesia) participants to transfer grammatical knowledge to new letter sets. Findings indicated that when tested with a different letter set than the one used for training, both amnesic patients and controls exhibited transfer (event though better performance was observed when letter sets at test were the same as training). Thus, overall participants learned both types of knowledge in AGL and additionally, each type showed independent effects indicating that it was likely mediated by separate neurocognitive systems. Neuroimaging evidence supports this general claim (Lieberman, Chang, Chiao, Bookheimer & Knowlton, 2004), indicating that rule-learning involves regions in the caudate nucleus whereas chunk strength learning is associated with regions of the medial temporal lobe.

To summarize, there are three different learning variables that participants are assessed on during implicit learning and statistical learning tasks (chunking, grammar learning, and probabilistic predictability) and these represent extraction of different information types in a sequence. The evidence suggests that learning can be isolated by the use of different types of tasks. It is possible that these three types of learning manifest differently in different populations such as typical vs. atypical readers, which is why it is important to investigate all three possibilities in the current study.

1.3 Are statistical learning and implicit learning the same phenomenon?

The literature on statistical and implicit types of learning started to overlap in such a way that researchers began to question whether the two were in fact separate processes or just one entity. Perruchet and Pacton (2006) proposed that statistical learning and implicit learning might be conceptualized as two approaches underlying a single phenomenon. This division is dictated by an apparent preference for chunking and grammaticality variables to be assessed in artificial grammar learning tasks that often measure implicit learning, whereas statistical learning studies tend to emphasize the importance of statistical probability. Perruchet and Pacton (2006) additionally suggested that, irrespective of the approach, the phenomenon under study can be thought of as a single type of domain-general incidental learning. Additionally, whether stimulus features are visual, auditory or tactile might also affect learning outcomes (such as modality effects; Conway & Christiansen, 2005). Other noteworthy points from Perruchet and Pacton's (2006) discussion include how associations between two or more units are formed, that is, whether statistical probability and chunk information are two distinct processes or whether they occur in succession during learning.

Apart from the views put forth by Perruchet and Pacton (2006), it is possible that implicit-statistical learning reflects deeper layers involved in acquisition of implicit sequence knowledge and these are conceptualized in **Figure 1.1**. Information or knowledge acquired from the environment may be organized based on task demands, specifically the artificial grammar learning task and other tasks embedded with statistical regularities. As reviewed earlier, the first type of task is associated with the learning of grammaticality information as well as chunking, and the latter with predictability. However, information learned as evidenced by these indices can be broken-down further according to Dehaene et al. (2015). For instance, in the current context, grammaticality contains underlying knowledge of order as well as algebraic patterns whereas transition-timing knowledge can be attributed to predictability (SRT, Hebb tasks, etc.).

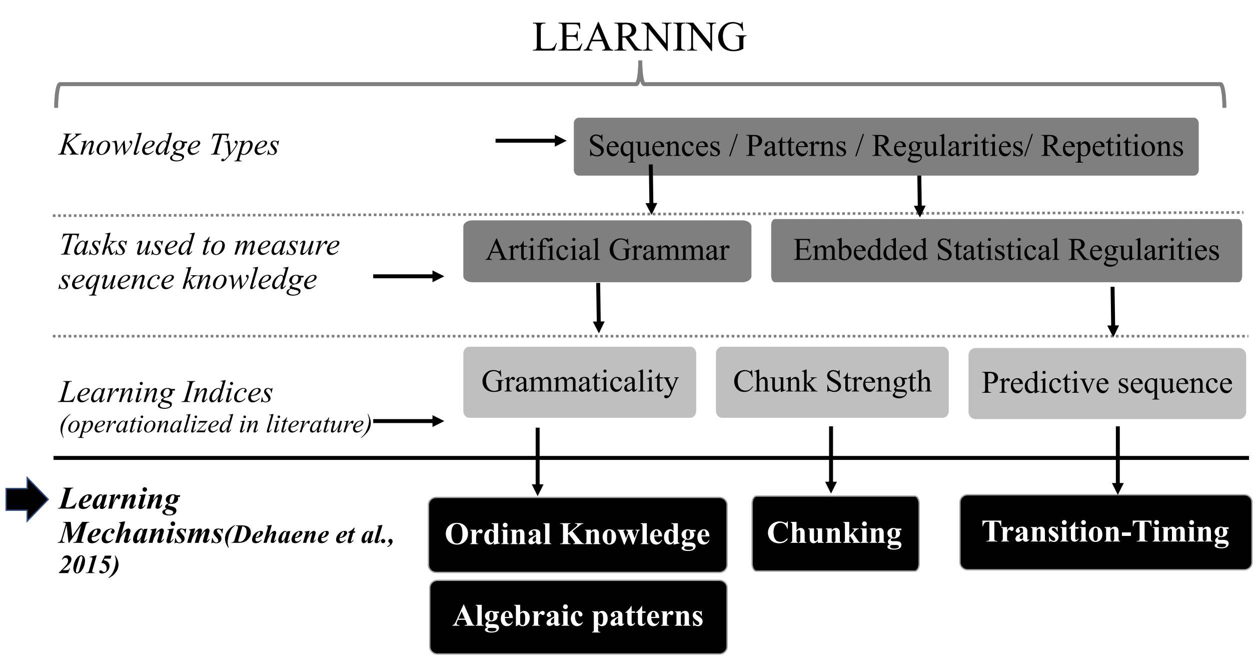


Figure 1.1Diagram showing learning outcomes by task

Thus, in keeping with terms used in previous research on artificial grammar and other statistical learning tasks (involving statistical probabilities), learning variables associated with each task in the current study were ‘grammaticality’, ‘chunking’ and ‘predictability’. However, Dehaene et al. (2015) have proposed a taxonomy of five distinct neural mechanisms related to encoding of sequences, namely: transition-timing, chunking, learning ordinal information, learning algebraic rules, and learning nested tree structures. Dehaene et al. (2015) further suggest that these five mechanisms operate independently of one another, each exclusively focused on acquiring information from the incoming sequence.

To sum up, there is a dearth of studies examining cognitive processes associated with statistical learning from the point of view of each type of statistical learning strategy (chunking, grammaticality, and predictability) in both typical and impaired readers. This study is designed to address these gaps in the literature between statistical learning and types of information learned based on the type of task used. Before addressing the details of the current study, a brief overview of theories of dyslexia along with previous findings on statistical learning and reading ability are presented in the next chapter.

Henceforth, the term ‘*implicit-statistical’* learning may be used to denote implicit/incidental pattern learning in the context of the current study; and when referring to types of knowledge obtained in each of the artificial grammar learning and other statistical learning paradigms, terms used are *ordinal* and *algebraic pattern* knowledge as well as *transition-timing* mechanisms, respectively (in line with Dehaene et al., 2015).

2 STATISTICAL LEARNING IN TYPICAL AND ATYPICAL READERS

This section includes a brief overview of prominent reading disability theories followed by a review of studies that examined statistical learning in adults and children with dyslexia.

2.1 Dyslexia: A Brief Description

The term *dyslexia* is a one-word substitute for an array of impediments characterized by poor word recognition, decoding, and spelling abilities. According to the diagnostic criteria of the DSM-5 (American Psychiatric Association., 2013), dyslexia would fall under the broader classification of ‘specific learning disorder’ (SLD). To be included within this category an individual must experience difficulties in learning and using academic skills, at least 1.5 standard deviations below norm for a given age level (Prelock, Hutchins & Glascoe, 2008), in areas such as mathematics, reading, or written expression. Thus in lieu of one single diagnosis, a person could be a candidate for a SLD diagnosis, but with added stipulations such as ‘impaired reading’, which could include problems with one or all of the following: word reading accuracy, reading rate or fluency, and reading comprehension. Unlike naturally emerging developmental milestones (e.g., speaking), academic skills (e.g., reading, spelling) are taught and deliberately learned. However, SLD (and dyslexia) is not defined as a result of poor instruction but occurs when there is a breakdown in typically acquired academic skills, despite sufficient opportunity for learning to occur.

Individuals with dyslexia appear to have systematic functional differences in their neurological composition (Norton, Beach & Gabrieli, 2015). For example, Shaywitz and Shaywitz (2008) explained that individuals with dyslexia have a distinct neural signature compared with good readers. The brain networks concerned with typical reading include three main regions: (1) an anterior system in the inferior frontal gyrus (Broca’s area), associated with articulation and word analysis; (2) one posterior system in the parieto-temporal region, associated with word analysis, and (3) another posterior system in the occipitotemporal region (the word-form area) associated with rapid and automatic word identification. In impaired readers, whereas the anterior system is slightly overactivated, the two posterior systems are underactivated (Shaywitz & Shaywitz, 2008).

This left lateralized posterior underactivation is known as *the neural signature for dyslexia*.

Dyslexia is most often found to be comorbid with other cognitive disabilities such as arithmetic learning disability (Dirks, Spyer, Lieshout & de Sonneville, 2008; Gross-Tsur, Manor & Shalev, 1996), attention deficit hyperactivity disorder (Pennington, Willcutt & Rhee, 2005; Gilger, Pennington & DeFries, 1992), specific speech disorder (Pennington & Bishop, 2009), specific language disorder (Catts, Adolf, Hogan & Weismer, 2005) and developmental coordination disorder (Kaplan & Norton, 1998). Thus, these patterns of comorbidity make it likely that, at least for some individuals with dyslexia, the problems are due to more general issues with attention, learning, memory, or other cognitive processes. A number of theoretical frameworks have been proposed to characterize the nature of reading difficulties in developmental dyslexia, which will be reviewed next.

2.2 Prominent Reading Disability Theories

The current view in the reading disability literature, especially that surrounding dyslexia, is that there is substantial support for the phonological deficit theory. This theory purports that atypical readers have an issue with the sound-to-phoneme mapping that typical readers learn during reading acquisition. The theory suggests that dyslexia is a language-based disorder characterized by difficulties in single-word decoding (Snowling, 1981) and phonological processing (Snowling, 2000). More specifically, phonological awareness is made up of phonemic awareness, which involves the ability to hear, extract and manipulate phonemes. It also requires an awareness of how well phonemes blend with other sounds [phonemes are the smallest units of sound (see the granularity theory by Ziegler and Goswami, (2005)]. This cognitive process, which occurs at the decoding level, warrants knowledge of letter-speech-sound associations (Froyen, Bonte, van Atteveldt & Blomert, 2009); and, as such, phonological awareness has been found to be highly automatic in good readers but less automatic for those with dyslexia, even in tasks involving a visual letter-speech-sound interference paradigm including both letters and letter-like stimuli (Bakos, Landerl, Bartling, Schulte-Körne & Moll, 2017). However, this prominent theory cannot always account for other low-level visual, sensory, and motor coordination deficits that have also been associated with dyslexia. Apart from phonological reasoning skills in those with reading impairment, it is also important to consider the influence of orthographic, procedural learning and statistical learning abilities that could also be contributing to the disorder.

The cerebellar deficit theory (Nicolson & Fawcett, 2001) assumes a very different way of conceptualizing reading impairments. Rather than suggesting a phonological deficit it postulates that a large majority of children with dyslexia show evidence of cerebellar abnormality as reflected by impairments in skill automatization, time estimation and most importantly, execution of an automatic sequence and error elimination.

In a similar vein, according to the procedural learning hypothesis, automatization is affected by procedural learning impairments and is suggestive of a more domain general, procedural learning impairment in those with reading disorders (Gabay et al., 2015; see also Krishnan, Watkins and Bishop, 2016). Procedural learning extends to cognitive and motor skill acquisition and refers mainly to the processing of sequences as well as coordinating learned ones such that the sequences become predictable over time and practice (Ullman, 2004).

The cerebellar and procedural learning deficit accounts seem to have some overlap; however, one way to distinguish cerebellar from procedural deficit accounts is that the former is primarily associated with cerebellar abnormality leading to problems with skill automatization, motor and articulatory issues - all resulting in either writing, reading or spelling difficulty (Nicolson, Fawcett & Dean., 2001) whereas the latter stems from issues with the procedural memory system as a whole. This memory system extends beyond the cerebellum to the basal ganglia, prefrontal cortex and motor areas (Ullman, 2004). Despite its implication in implicit learning (Nicolson, Fawcett & Dean., 2001), the amount of cerebellar activation during implicit learning tasks is still debatable (Witt, Neuschman & Deuschl, 2002) and as such it is difficult to know the exact role the cerebellum plays in implicit learning and statistical learning processes. On the other hand, the procedural memory system as a whole could be thought of as a type of implicit learning.

Finally, according to the temporal processing deficit account, children with dyslexia have trouble integrating sensory (visual) information, especially when it is presented rapidly (Conlon, Wright, Norris & Chekaluk, 2011). As a benchmark, Chiappe, Stringer, Siegel & Stanovich, (2002) have shown that skilled readers would require an inter-stimulus interval of at least 30ms to differentiate between two stimuli presented in rapid sequence. But studies involving participants who experience reading difficulties suggest a syntactic processing weakness for individuals with dyslexia during a fast-paced reading task (Breznitz & Meyler, 2002). More specifically, Cohen-Mimran, (2006) reported accuracy differences depending on the inter stimulus intervals (ISI) during tasks. ISI is the time interval between the offset of one stimulus and the onset of another, typically during tasks where items are serially presented to the participant. They found significantly lower accuracy for children with dyslexia on a task with a short ISI (50ms) compared to a longer ISI (500ms).

Thus, regardless of which theory the disability pertains to, problems with reading print might ensue at any point after lexical access, because deficits in those with reading disorders have been found at various points - at the auditory-only level (Wright, Bowen & Zecker, 2000) or even on tasks involving visual symbol search (Jones, Branigan & Kelly, 2008). One theme common to cerebellar, procedural and temporal deficit theories of reading disability is that these theories all pertain to issues underlying sequence processing. Such pattern or sequence processing is clearly related to statistical learning. Hence, based on these theories and the link between reading ability and statistical learning, it would not be surprising if a statistical learning deficit was observed in individuals with reading disability.

2.3 Literature Review with Statistical Learning Paradigms

Recent review and empirical articles have summarized contemporary findings that very generally link SL with reading ability (Arciuli, 2018). However, some others have focused specifically on the relation between SL and dyslexia (Banai & Ahissar, 2018; Sawi & Rueckl, 2018; Schmalz et al., 2017) some of these articles are discussed below.

Figure 2.1 below shows details of participants in studies using paradigms that refer to patterned input as having either an artificial grammar or sequences with predictive probabilities (i.e., transitions and timing information) embedded within the task. **Figure 2.1** also indicates whether children or adults were included in each study, the sensory modality engaged during the task, stimuli features and additional study design details; all studies compare typical to atypical readers.

In **Figure 2.1**, the first column breaks down the ways in which studies may be categorized. For instance, (in order from top to bottom) studies can differ based on degree of impairment. Here the ‘other group differences’ pertains to studies which showed intact learning (i.e. no statistically significant group differences) but did mention instances of group differences such as slower RTs for impaired readers. This is followed by categorization based on sensory modality involved in the task and then the nature of the stimuli. Next, ‘input’ refers to the type of task used in the study, such as artificial grammar learning tasks or sequence related tasks from the family of SRT/ Hebb (red) and other tasks also relying on transition and timing knowledge (blue). The final category refers to duration of study and indicates studies that were spread over more than one session.

Research studies depicted in **Figure 2.1,** show that some studies have specifically used artificial grammar learning paradigms (e.g. Schiff, Katan, Sasson & Kahta, 2017; Kahta & Schiff, 2016) and others have used other paradigms containing statistical regularities/transition-timing information (e.g. Bennett et al., 2008; Du & Kelly, 2013; Rüsseler, Hennighausen, Münte & Rösler, 2003) and some have incorporated both paradigms (Laasonen et al., 2014; Nigro, Jiménez-Fernández, Simpson & Defior, 2016). Whereas some studies in **Figure 2.1** have shown impairments in participants with dyslexia compared to typically reading matched controls (e.g. Du & Kelly, 2013; Gabay et al., 2015; Howard, Howard, Japiske & Eden, 2005; Kahta & Schiff, 2016; Schiff et al., 2017), others have shown no impairments (e.g. Bennett et al., 2008; Inacio et al., 2018; Roodenrys & Dunn, 2008; Rüsseler et al., 2006; Samara & Caravolas, 2017). A few studies also reported minor differences in performance across groups (e.g., slower RTs for those with dyslexia or other discrepancies) even though they found intact implicit-statistical learning otherwise (Bennett et al., 2008; Nigro et al., 2016).

Additionally, studies can also be separated by stimulus type. For instance, some have used linguistic stimuli (Gabay et al., 2015; Vandermosten, Woters, Ghesquière & Golestani, 2018) and others have used non-linguistic symbols (Howard et al., 2005) or both (Bennett et al., 2008). But if broken down by stimulus used – there seems to be little conclusive evidence showing that linguistic stimuli yield a learning impairment more so than non-linguistic stimuli. For instance, of the tasks that used linguistic stimuli, some studies reported impaired learning (Jones et al., 2018; Kahta & Schiff., 2016) and some did not (Bennet et al., 2008).

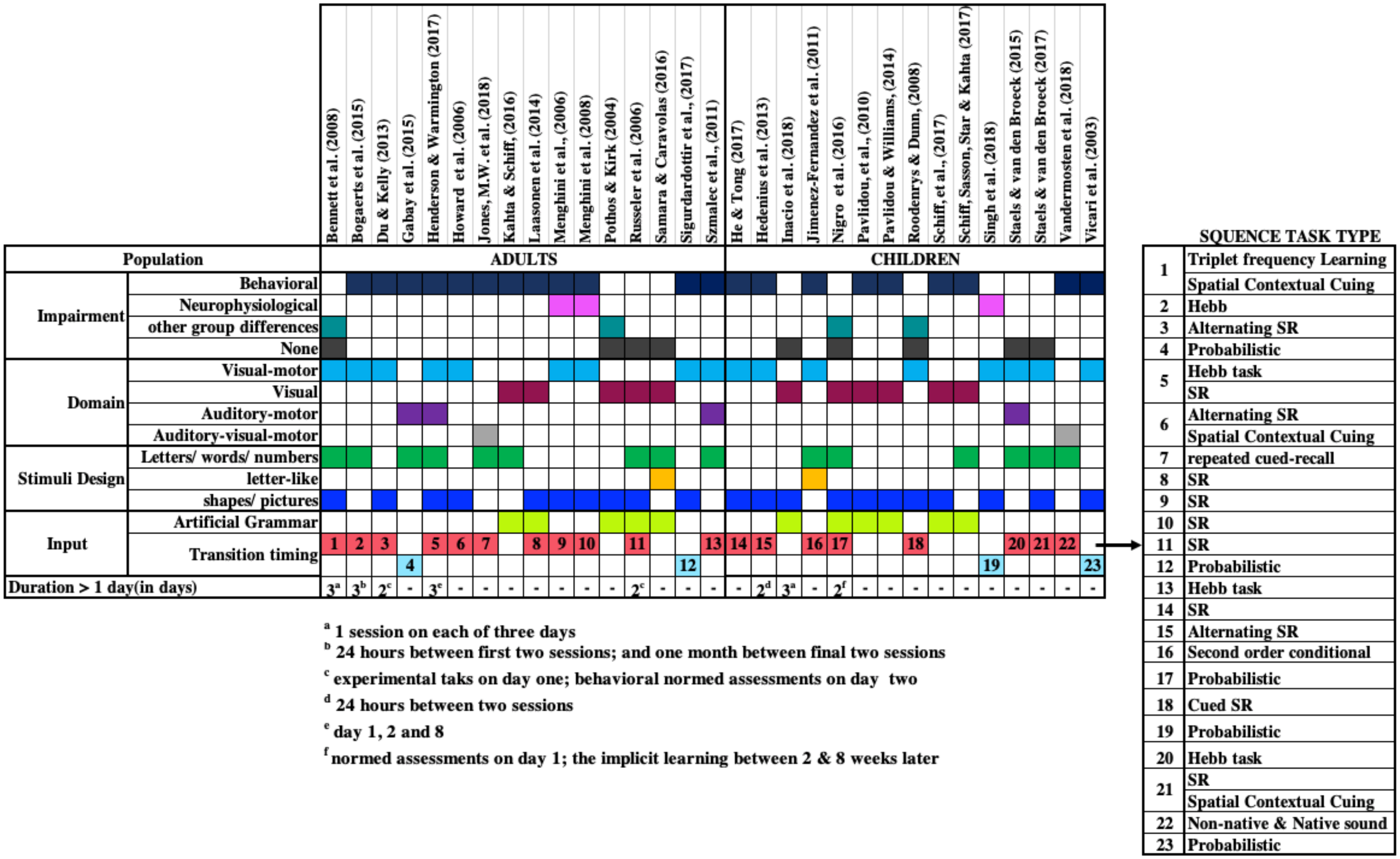


Figure 2.1Empirical Literature Review of Implicit-Statistical Learning and Dyslexia Research

Similarly, some studies using non-linguistic stimuli showed impairment for atypical readers (Menghini et al., 2008; Pavlidou & Williams, 2014; Sigurdardottir et al., 2017; Singh et al., 2018; Vicari et al., 2003), or no impairment at all (Pothos & Kirk., 2004; Roodenrys & Dunn., 2008; Rüsseler et al., 2006; Staels & van der Broeck, 2017). Of particular relevance to the present investigation are findings reported by Nigro et al. (2015), who found no advantage for either linguistic or non-linguistic stimuli despite conducting one experiment using both types of stimuli to investigate statistical learning impairment in typical vs. atypical readers. Additional studies using non-linguistic stimuli in study designs might help clarify whether individuals with reading disability have an impairment specifically for linguistic material or whether it extends to non-linguistic input as well.

On inspecting **Figure 2.1**, there seems to be a higher number of visual and visual-motor paradigms compared to tasks focusing on other domains. All but one study (Staels & van den Broeck., 2015 had two task versions) that reported no impairments were based on visual and auditory task paradigms. Also, a majority of the AGL paradigms were administered in the visual (compared to auditory) domain. This shows that modality type could also be influencing statistical learning ability but more research across all the domains equally, is required before drawing such a conclusion.

With regards to experimental groups based on (non-overlapping) diagnostic criteria only Laasonen et al., (2014) accounted for a separate group with ADHD symptoms --- while this may help account for the influence of attention deficits, is not necessarily the only way to study learning in a reading disordered population. This is because it is also possible to view deficit on a continuum from poor to excellent as is evident in the reorganization of neurodevelopmental disorders within DSM-5. In fact, it seems hard to isolate the influence of all other cognitive deficits and focus solely on reading difficulties. It is perhaps even contradictory to the multi-etiological nature of dyslexia (within the framework of SLDs) because controlling for one type of comorbidity does not solve the issue of other comorbid diagnoses. It should be mentioned that Pothos et al. (2004) did check for the presence of ADHD symptoms as well. Also, worth noting, is that in the studies that did not report any impairments for adults, intact learning could be due to the fact that these adults had received some remediation and have slightly improved reading ability compared to children.

Some additional studies not included in **Figure 2.1,** because they did not specifically compare individuals with and without dyslexia, are nonetheless worth mentioning. Ise, Arnoldi, Bartling and Schulte-Körne, (2012) showed a learning deficit for children with a spelling disability, during an artificial grammar learning task. They found that poor readers had difficulty recognizing old letter strings (from the familiarization phase). These poor readers showed impaired learning for frequent letter chunks especially in strings that were phonologically accessible. However, they created a grammar different from the Knowlton and Squire (1996) grammar and did not use a balanced chunk strength design. Rosas et al. (2010) recreated a child-friendly version of an artificial grammar learning task with non-linguistic visual stimuli and investigated grammaticality but not chunk strength. They found that group differences (between those with and without ADHD) were observable at the electrophysiological level as well as for behavioral RTs, but not for accuracy. In fact, children with ADHD outperformed those without an attention deficit. In addition, van Witteloostuijn, Boersma, Wijnen & Rispens, (2017) conducted a metanalysis on learning in dyslexia across the developmental lifespan. A sub-section of the studies represented in **Figure 2.1** comprises their analyses. They concluded that individuals diagnosed with dyslexia showed a greater impairment than those without dyslexia, particularly in children (compared to adults). Another metanalysis (Lum, Ullman & Conti-Ramsden, 2013) showed that individuals with dyslexia showed poorer learning abilities than controls, as indexed by sequence learning on the SRT task. Also, noteworthy, is that some studies (as is indicated in **Figure 2.1**) also incorporated more than one experimental session compared to others. This indicates that not all studies are equal in terms of consolidation between sessions and that this may have influenced learning over time.

Thus far only a few studies have centered on neurophysiological indices of learning when investigating the link between statistical learning and dyslexia. For instance, Singh et al. (2018) used a visual statistical learning paradigm to examine learning of serial transition probabilities with electroencephalography (EEG) recordings. They found that the children with dyslexia exhibited a different neural signature than the typical readers. This meant that when participants' neural responses to a given stimuli of interest (event related potentials; ERPs) were averaged --- they displayed a very different learning pattern from their counterparts, suggesting delayed statistical learning. The P300 --- or neural signature reported by Singh et al. (2018) has been associated not only with learning but also the ability to predict an upcoming stimulus. Also noteworthy is the fact that the behavioral results indicated relatively intact statistical learning for both groups (Singh et al., 2018). This highlights the fact that statistical learning outcomes might be manifested differently when assessed by behavioral vs. neurophysiological indices. One reason for this is that the children with dyslexia in the study might have exhibited intact implicit-statistical learning but might have also had delayed attention-dependent predictive processing that manifested via ERPs. This is based on the sluggish attention allocation to stimuli cued by a predictive target (Hari, 2001).

To conclude, there is clearly evidence for statistical-learning difficulty in those with reading disability across the developmental lifespan. However, there are not many studies designed to examine the different types of information learned in each type of task. These points are briefly discussed in the next section.

2.4 Unanswered Questions: Statistical Learning and Reading Ability

Previous research has not fully investigated to what extent individuals with reading disability acquire different types of information as a function of the particular task that was used. For instance, it would be beneficial to incorporate tasks that each demand different learning indices, such as grammaticality and chunk strength from an artificial grammar learning task and predictability via alternative sequence-based learning paradigms. Here, as in **Figure 1.1**, grammaticality, chunk strength and predictability are just terms consistent with learning variables used in the current task but the information type underlying each variable is as per Dehaene et al. (2015); that is, grammaticality is associated with ordinal and algebraic pattern knowledge, chunk strength with chunking and predictability with transition-timing.

Additionally, it is important to control for the type of stimuli (i.e., either linguistic or non-linguistic) and perceptual domain (auditory or visual). Together, such a design could elucidate processes underlying implicit-statistical learning in individuals with a reading disability and help uncover whether acquisition of specific information types during learning might be more or less impaired than others.

The added advantage of using non-linguistic material is that it will help to determine whether the deficits are due to general (non-linguistic) cognitive processing/learning vs. being specific to linguistic/phonological material. Findings from such a study would help pinpoint which (if any) learning strategy is atypical in dyslexia. In addition, although there is research suggesting that statistical learning ability is mediated by awareness levels (Kahta & Schiff, 2016; Singh et al., 2017; Turk-Browne, Scholl, Chun & Johnson, 2009), few studies have examined whether awareness levels during statistical learning might differ between those with and without reading disabilities.

Finally, there is no known behavioral and ERP study involving administration of both types of tasks mentioned above in the same population of adults with and without reading disorders. Of the recent studies, only a few have used neurophysiological measures in addition to behavioral responses (Ahissar & Jaffe-Dax, 2018; Feng et al., 2017; Rüsseler et al., 2006; Schulte-Körne et al., 2004). In addition to behavior, it is important to investigate neural processes associated with statistical learning in atypical readers, as these brain measures will help inform our understanding of the disorder (and might even help disambiguate among the different theories of dyslexia). Often, behavioral and neural mechanisms complement each other but are manifested differently (Batterink et al., 2015). For instance, the temporal precision provided by ERPs, might indicate speeded target detection/motor response but corresponding behavioral responses might show poor accuracy or slow RTs. Thus, the literature would benefit from the collection of both behavioral as well as neurophysiological data.

2.5 The Current Study Aims

1. To examine whether adults diagnosed with a reading disorder show an implicit-statistical learning deficit using non-linguistic stimuli as measured by both behavioral RTs and ERPs, using: (a) a transition-timing and (b) an artificial grammar paradigm.
2. To examine whether this deficit is specific to the type of learning occurring in each task: (a) Transition-timing, (b) grammaticality learning, or (c) chunk learning
3. To examine whether implicit-statistical learning ability is correlated with reading ability scores from normed behavioral assessments.

4. To determine whether the learning deficit is more pronounced in any one modality (visual/ auditory) over the other.
5. To examine whether implicit-statistical learning ability depends on awareness of the underlying patterns, i.e. whether learning is implicit or explicit and whether awareness levels differ between typical and atypical readers.

2.6 Hypotheses

1. For both learning tasks, indication of a learning deficit (for atypical readers) is expected, as measured by both behavioral RTs and ERPs respectively.
2. Atypical readers are expected to show impairment on at least one but possibly all three learning outcomes/ variables.
3. In line with previous studies (Bennett et al., 2008; Conlon et al., 2011 and Gabay et al., 2015) findings should reveal significant correlations between statistical learning and performance on normed neuropsychological assessments suggesting that implicit-statistical learning performance influences word reading ability.
4. Awareness levels might differ between the two groups with reading disorders, which in turn might help determine whether learning impairments in those with reading disability are based on levels of awareness of the underlying implicit-statistical patterns.

Because learning was indexed neurophysiologically by event related potentials (measured neural signals from the cortical surface, produced in response to a specific event/stimulus of interest). Additionally, learning was also indexed behaviorally by RTs. If participants indicate difficulty in learning statistical-sequential visual regularities by way of neural ERPs (compared to behavioral responses), it could mean that incoming information is being processed differently. ERPs can account for observed neurophysiological deficits – for example, indexing attention/

explicit processing, whereas RTs might reflect more implicit processing (Batterink, Reber, Neville & Paller, 2015).

3 METHODS

3.1 Participants

Participants were comprised of two main groups. The description for each group is presented below along with the exclusionary criteria for each group and the recruitment sources.

3.1.1 *Atypical Readers: [Adults with a reading disorder + Comorbid symptoms]*

Sixteen English-speaking adult (20 to 65 years of age) participants were recruited mainly from the Regents Center for Learning Disorders' (RCLD, at Georgia State University) database, as well as from the general public. These volunteers were compensated at $50 each for their participation. Participants were recruited on the basis of a reading disorder diagnosis (which also included comorbid diagnoses such as, but not limited to, attention deficit disorders, dyscalculia, bipolar disorder, depression, and anxiety disorder). Exclusionary criteria involved any visual or auditory impairment, a RCLD diagnosis more than 5 years old and inability to travel to the Georgia State downtown campus for participation.

Initial RCLD recruitment comprised a database of approximately 100 participants that fit the inclusionary criteria. From this list of potential participants contacted by authorized personnel in the RCLD, 66 were willing to be contacted further for recruitment. From this new subset, only 19 responded to correspondence regarding the study. Of these only 13 finally consented to participate in the experiment.

Apart from the RCLD, participants were also recruited from the general public using the same inclusionary criteria described above. A study flyer was posted internally through Georgia State University's psychology listserv for further recruitment purposes. Additionally, the study was advertised through the Office of Disability Services on campus, as well as by word-of-mouth. These approaches resulted in recruitment of 3 more volunteers, which resulted in a total of 16 participants. Appendix A.6 contains all participant-specific demographics.

3.1.2 *Typical Readers*

For the typical-reader group, 37 English-speaking adults (18 to 29 years of age) with no diagnosis of a reading disorder or any other similar cognitive diagnoses were recruited from the SONA database (at Georgia State University) and matched with their counterparts on scores related to working memory (explained below). Of these, only 36 adults successfully completed the entire experiment. They were compensated with class credit for participation. Exclusionary criteria involved any visual or auditory impairment or other diagnoses (e.g., ADHD, etc.).

Table 1 Demographic characteristics of the groups

		Group			
		Typical		Atypical	
N		36		16	
Age in years[1]		19.990	2.672	31.795	14.177
Digit Span[1]		26.611	4.486	24.812	4.415
Sex[2]	Male	8	22.2%	6	37.5%
	Female	25	69.4%	10	62.5%
	Nondisclosed	3	8.3%	0	0%
Handedness	Left	0	0%	1	6%
	Right	32	88.9%	11	68.8%
	Ambidextrous	4	11.1%	4	25%

[1] Mean with standard deviation; [2] Frequency with percent.

As is evident in Table 1, according to a non-parametric Mann-Whitney (Mann & Whitney, 1947) test there was an age disparity between the two groups with the atypical readers being older on average than the typical readers [$U = 41.00$; $p < .001$]. Only 3 atypical participants were flagged as age outliers but even when removed, Mann-Whitney test results consistently indicated statistically significant group differences due to age variability amongst atypical readers [$U =$

41.000; *p*< .001]. Therefore, all atypical participants were retained in future analyses and, wherever possible, checked for age-related correlations against relevant outcome measures. For additional demographics on all participants, refer to ***Appendix A.1***; the participant information questionnaire used to obtain these demographics is in ***Appendix B.1***.

3.2 Materials and Procedures

All participants were administered Informed Consent documents. Upon granting consent to proceed they also completed a participant information questionnaire (***Appendix B.1)***, the Adult ADHD Self-Report Scale (Kessler et al., 2005; ***Appendix B.2***), the Brain Mapping Handedness Inventory (***Appendix B.3***), and the Ollen Musical Sophistication Index (Ollen, 2006; OMSI, ***Appendix B.4***). These materials are briefly discussed below.

All participants completed three computer-based learning tasks lasting approximately 30 minutes each. In these tasks, each participant was presented with shapes on the screen or tones via computer speakers. After viewing/listening to these stimuli, participants either had to: (1) reproduce a certain string of shapes (via mouse clicks) and make a judgment regarding previous stimuli; (2) detect (via button press) a certain shape; or (3) detect (via button press) a certain tone. Descriptions of the computerized artificial grammar learning and the sequence based (transition-timing) visual and auditory implicit-statistical learning tasks are presented below. The order of presentation of the three computerized tasks was counterbalanced across participants.

Computerized assessments were followed by the administration of a feedback questionnaire containing pattern awareness questions (see ***Appendix B.5***), after which behavioral assessments were administered to participants individually by trained personnel. These assessments contained normed measures of reading, spelling and cognitive processing. During these assessments, electrophysiological data was not collected.

For both tasks, stimuli were presented electronically using E-Prime 2.0.8.90 software (Psychology Software Tools, Pittsburgh, PA), on a Dell Optiplex 755 computer. All visual and auditory stimuli (**Figure 3.1**) were non-linguistic.

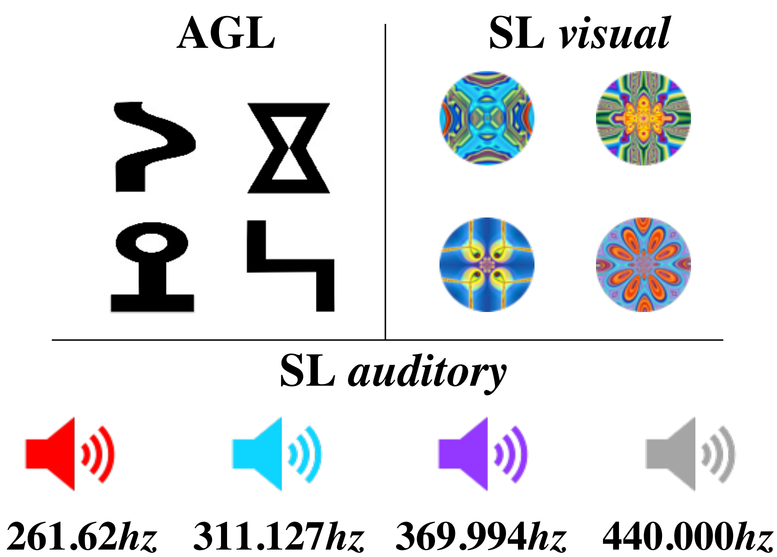


Figure 3.1 Stimuli used in the artificial grammar learning and visual and auditory implicit-statistical learning tasks (Stimuli from Schapiro, Rogers, Cordova, Turke-Browne & Botvnick, 2013)

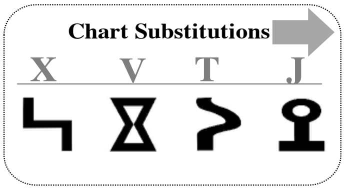
3.2.1 *Artificial Grammar Learning Task (Visual)*

This task used a balanced chunk-strength design (see *Introduction*; Knowlton and Squire, 1996) in order to assess chunking as well as ordinal and algebraic-pattern learning. In a typical artificial grammar learning design (i.e., no control over chunk strength), chunk strength of grammatical items is higher than nongrammatical items because nongrammatical items contain (incorrect) chunks that do not occur during the training phase. However, to examine the effects of chunk strength and grammaticality independently of one another, test items were created in a balanced chunk-strength design such that grammatical and nongrammatical items had equivalent chunk strength. Thus, grammaticality and chunk strength of the test items were not confounded.

3.2.1.1 *Materials*

Based on Knowlton and Squire (1997), the symbol strings were generated by a finite-state grammar that determined the order that different elements could occur in the sequence embedded in the stimulus presentation. Using this exact (Knowlton & Squire, 1997) grammar, but replacing the letters with symbols taken from Schapiro et al., (2013) shown in **Figure 3.2**— (randomly assigned for each participant)—23 training items and 16 test items were generated. The symbol strings were two to six items in length. The set of nongrammatical items were created by introducing an error into each of the sixteen grammatical items. Finally, 16 test items were generated, ensuring that chunk strength was equal across grammatical and nongrammatical items. In the current task, this original number was doubled to 32 (i.e., 32 trials per testing block).

As per Knowlton & Squire's (1997) calculations, test chunk strength was obtained by averaging associate strengths of each chunk in the items. The quantity of high and low chunk strength items among both grammatical and nongrammatical items were approximately equal. Average chunk strength was 7.2 For grammatical items and 7.0 for nongrammatical items. **Figure 3.2** lists the test items that were used within each of the four categories: (1) grammatical with high chunk strength, (2) grammatical with low chunk strength, (3) nongrammatical with high chunk strength, and (4) nongrammatical with low chunk strength.



Abbreviations
Grammatical – High chunk strength (**GH**)
Grammatical – Low chunk strength (**GL**)
Non-Grammatical – High chunk strength (**NGH**)
Non-Grammatical – Low chunk strength (**NGL**)
chunk strength (*CS*).

Training Items

XXVT	VXJJJJ	XXVJ	VJTVXJ
XXVXJJ	XVT	VJTVX	XXXVX
VXJJ	XXXVT	VJTVJ	VJTXVJ
XVJTVJ	VJ	XXXVTV	XVXJ
XXVXJ	XVXJJJ	XVXJJ	XXXXVX
XVX	VJTVTV	VT	

Test Items

GH	*CS*	GL	*CS*	NGH	*CS*	NGL	*CS*
XXXVXJ	10.4	VJTVT	6	VJTV	7	XXJJ	6.8
XVTV	6.8	VTVJJ	5.1	XXV	12.3	VXJTJ	4.9
VXJ	9.3	VTVJ	5.6	XVXV	10	XXVVJJ	6.2
XXVTV	8	XVJTVT	6.7	XVXVJ	9.1	JXVT	5
XVJTVX	7.4	VTV	5	XXVJJJ	7.8	XXTX	2.8
XXVTVJ	7.7	XVTVJ	6.7	XJJ	7	TVJ	6.7
VJTXVX	6.8	XVTVJJ	6.1	VXVJ	8.2	VXJJX	5.9
VX	12	VTVJJ	5.2	XVXT	7	VJJXVT	4.9
M	**8.6**	***M***	**5.8**	***M***	**8.6**	***M***	**5.4**

Figure 3.2 Knowlton and Squire's, (1997) artificial grammar diagram used for item creation; Left Panel: Symbol Substitutions for letters and Abbreviations referred to in the table.

3.2.1.2 ***Procedure***

The artificial grammar learning task comprised of three phases: practice, exposure, and test. Practice was used to introduce the participant to the task. Exposure was meant to familiarize the participant with symbol strings generated from the grammar. Test was designed to assess whether participants could discriminate between symbol strings that followed the rules of the grammar compared to those that did not. Symbols used in this task were chosen from a set of symbols created by Schapiro et al. (2013; see Figure 3.1).

Presentation of each item (i.e., individual symbol within the string) during practice and training was self-paced; that is, participants were presented with each symbol string and were instructed to reproduce it via left mouse click. All trials were dark items presented on a white background. On every trial the four symbol options were always within view for the participant to refer to at the bottom of the screen. The participant only had to choose (by clicking) the desired symbol to reproduce each item above the pre-existing options. Upon reproduction the participant received feedback regarding accuracy of their response. After making their selection, the participant could click one of two on-screen options: ‘enter’ or ‘cancel’. Clicking ‘enter’ meant submitting the response whereas ‘cancel’ was used to erase the most recently clicked item option(s). Once submitted, participants advanced to the next symbol string if their responses were accurate, but they received an error message and were prompted to reproduce the item once again if the responses were inaccurate. Thus, the participant was not permitted to move on to a subsequent symbol string without reproducing the current string accurately.

The task began with eight practice[1] trials during which the participant was familiarized with the task before the training phase. During practice, the participant was given instructions on how to respond via mouse click. Similarly, the subsequent training phase began with the presentation of a string of symbols (as in **Figure 3.3**) that the participant was asked to reproduce on the screen via mouse click. The number of total trials at training was four times that of the original Knowlton and Squire (1996) experiment to increase exposure before the test phase. Training comprised of 4 blocks of 23 trials (or a total of 92 self-paced trials) separated by three 30-s breaks.

After exposure, the test phase began. The participant was informed that items in the training item strings were created according to a structured “pattern”; and that they would then see new item strings (same items, new sequence combinations) regarding which they must make a judgment decision as to whether the item string was generated by the same rule or not. Every test trial began with a fixation cross for 500ms followed by a white screen for 100ms. This was followed by presentation of the novel symbol sequence for 2000ms after which the grammaticality judgment question was presented followed by the participant’s correctness rating. They first

[1] Each practice trial was made up of a string that was 6 items long, using the same symbols as the rest of the task but did not follow the Knowlton and Squire (1997) grammar and were designed only to help familiarize the participant with task demands.

indicated their grammaticality judgment response by pressing: (1) if the item followed the rule and (4) if it did not follow the rule. They then rated the confidence in their own judgments using the following numbered response button options: (1) I was guessing, (2) I was mostly guessing, (3) I was mostly sure or (4) I am sure. Participants did not have to memorize the response button (numbered) options for any of the questions as these instructions were always be present at the bottom of the screen. Testing comprised of 4 blocks of 32 trials (or a total of 128 self-paced trials) separated by three 30-second breaks. Test items were presented in a random order. See **Figure 3.3** (above) for a schematic representation of a single trial at training and test. During test, participants responded via button box. Numbered keys corresponded to the numbered options on-screen so participants did not need to memorize any pairings or combinations.

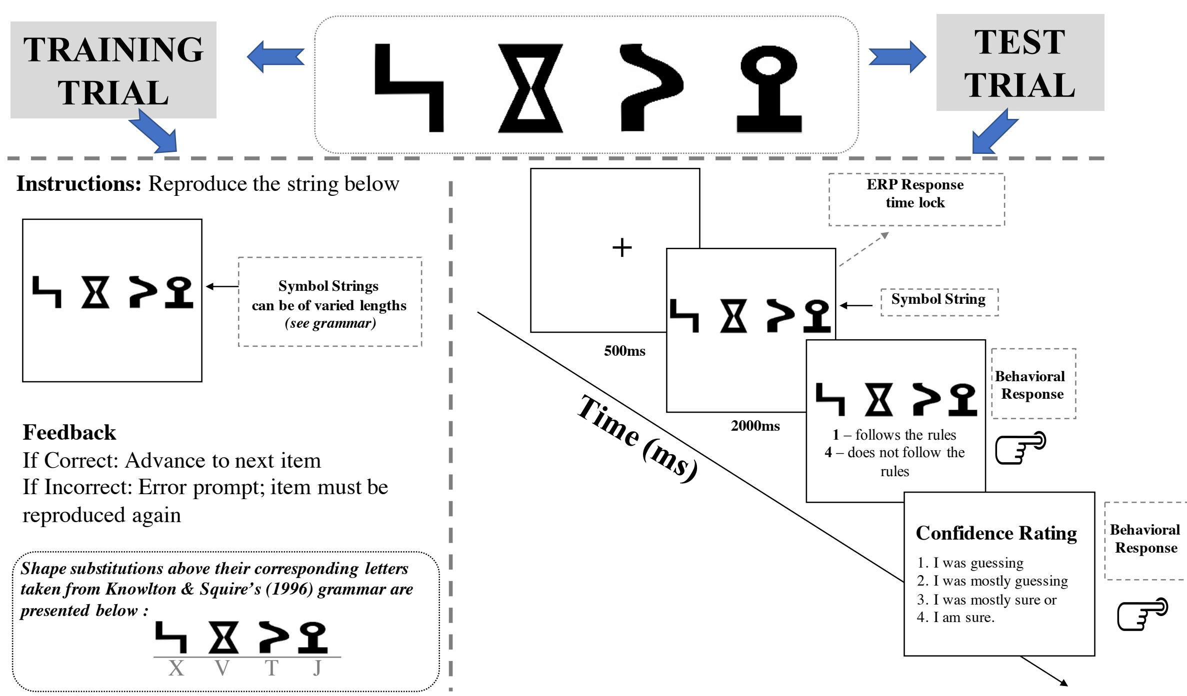


Figure 3.3Artificial grammar learning task. Left panel: Schematic representation of training trial; Right panel: Schematic representation of test trial.

3.2.2 *Visual-motor Statistical Learning*

This task was meant to measure visual statistical transition-timing information and is and is similar to the task used by Jost et al., (2015), except the colored circles in Jost et al, (2015) were replaced by textured circles from Schapiro et al., (2013), and are presented in **Figure 3.4** below. The task consisted of a few practice trials followed by the two main phases of testing. Practice was designed to introduce participants to the task. Phase 1 was meant to familiarize the participant with the probabilistic rules, or nonrandom task sequences. It was designed to assess whether participants had learned the predictor - target contingency rules (i.e., using RTs and ERPs to measure learning of the predictor-target contingencies) – during which the target stimulus would be preceded by a stimulus that was highly predictable (90%) or by a stimulus low in predictability (10%). During Phase 2, these predictability conditions switched to 50% probability and participants were assessed on their ability to detect the new equal predictability conditions as opposed to high/low predictability from Phase 1 training.

3.2.2.1 *Materials*

Stimuli in this task (see **Figure 3.4**) followed a pre-defined structure based on statistical probability of appearance. On every trial, 1 to 7 *standard* stimuli could first appear, this was followed by any of two *predictor* stimuli: high and low. Predictor stimuli may or may not have been followed by a *target* stimulus. In the high predictability condition, a high probability (HP) predictor was followed by the target 90% of the time or by a standard stimulus 10% of the time. In the low predictability (LP) condition, the target/standard probabilities were reversed. The task had two parts or phases, explained below. Each stimulus was randomly assigned (as target/standard/HP/LP) for every participant. Target assignment was at the outset of the experiment and once selected, was applied across the entire experiment for that participant.

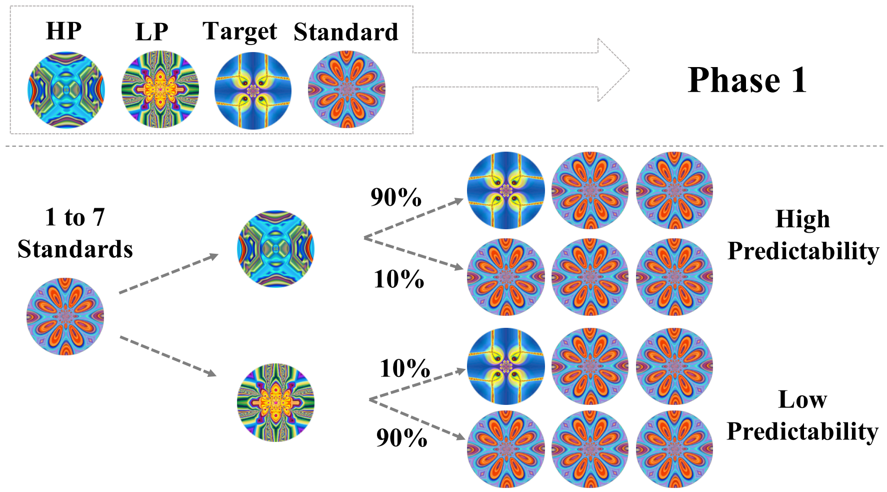


Figure 3.4 Probabilistic visual statistical learning task. Upper panel: Stimuli --- from Schapiro et al. (2013); Lower panel: Schematic representation of a training trial.

3.2.2.2 ***Procedure***

The participant first got acquainted with the task through four practice trials. Practice trials (for visual and auditory task versions) were randomly presented, always seven items long and made up of the same stimuli as the rest of the task and were designed only to help familiarize the participant with task demands. Participants were instructed to press a response button as soon as they saw the target shape (see **Figure 3.4**). Speeded and accurate responding was emphasized in the instructions.

After practice, the participant began Phase 1. Each block comprised of 20 trials for a total of 60 trials that were presented across 3 blocks (10 trials per predictor). Within each block, trials were presented randomly and in a continuous fashion such that the participant was unable to distinguish one trial from another. A break lasting a minimum of 30s separated each block. All visual stimuli were presented in white in the center of the computer screen on a light background. Stimuli were displayed for 500ms, followed by a dark screen, which was displayed for an additional 500ms (inter-stimulus interval was 500 ms; stimulus onset asynchrony was 1000-ms).

Phase 1 was followed by a Phase 2, during which the predictability conditions changed from training, so that the probability of a target following a predictor remained at 50% (see **Figure**

3.5). Each block comprised of 20 trials for a total of 120 trials that were presented across 6 blocks (10 trials per predictor). This means that in Phase 2, there were two types of trials: ones that were consistent with the probabilities to which participants had experienced during training, and ones in which there was a violation of expectation (LP occurred *more* frequently and HP occurred *less* frequently than in Phase 1, but both occurred with equal frequency in Phase 2). Trial presentation and participant responses were exactly the same as during training. Participants were never informed of the change in the probabilistic nature of the task, or even that there were statistical probabilities at all. Each block was followed by a 30s break.

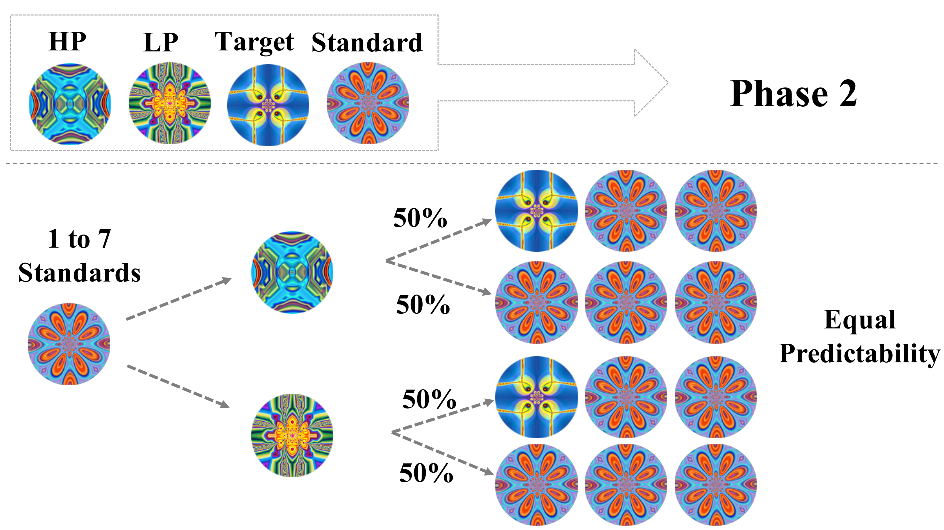


Figure 3.5 Probabilistic visual statistical learning task. Upper panel: Stimuli --- from Schapiro et al. (2013); Lower panel: Schematic representation of a test trial.

3.2.3 ***Auditory-motor Statistical Learning***

This task was created with the same structure as the visual-motor task above but with pure tones (Saffran et al, 1999) in place of the abstract circles. Similar to the previous tasks, practice trials were administered briefly to introduce participants to the task. Phase 1 was meant to familiarize the participants to the probabilistic regularities, and Phase 2 was designed to assess whether participants had learned the regularities during training and could detect violations of the predictability conditions that they had been exposed to during training.

3.2.3.1 *Materials*

Similar to Saffran et al., (1999) stimuli were constructed out of four pure tones (261.62*Hz*, 311.127*Hz*, 369.994*Hz*, and 440.000*Hz*) of the same octave (starting at middle C within a chromatic set), using the sine wave generator in Audacity 2.0.5. The pure tones (between 45*dB* and 60d*B*) were each the same length (0.5s) as each other and also corresponded to the duration of visual stimulus presentation (used in the previous task). **Figure 3.6** shows the stimuli layout for the audio Phase 1 **Figure 3.7** displays the layout for Phase 2.

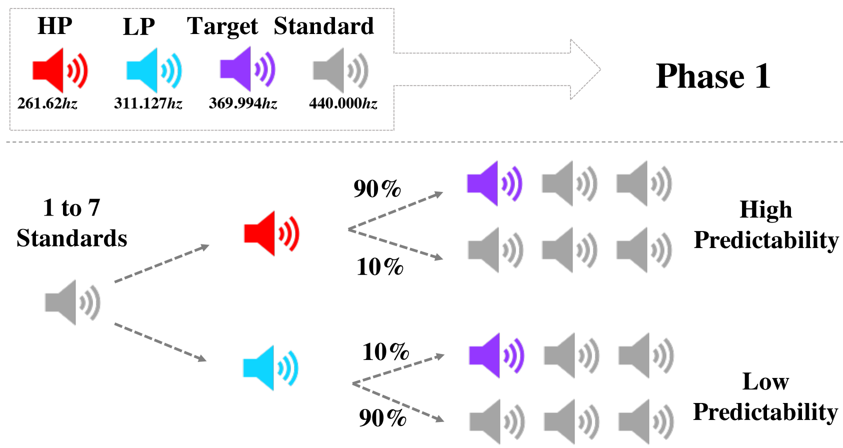


Figure 3.6 Probabilistic audio statistical learning task. Upper panel: Stimuli --- from Saffran et al. (1999); Lower panel: Schematic representation of a training trial.

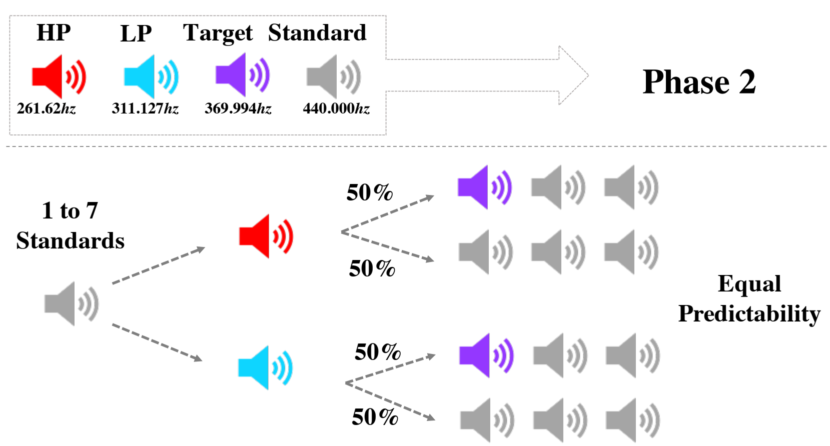


Figure 3.77Probabilistic audio statistical learning task. Upper panel: Stimuli --- from Saffran et al. (1999); Lower panel: Schematic representation of a test trial.

3.2.3.2 ***Procedure***

The structure, trial presentation and participant responses (button press) for the auditory statistical learning task were exactly the same as for the visual-motor SL task. For this task, participants were instructed to press the button as soon as they *heard* the target sound. Auditory stimuli were presented at the same *dB* level for all participants via computer speakers on either side of the computer screen. Each stimulus was randomly assigned as target/standard/HP/LP for every participant. Target assignment was made at the outset of the experiment and once selected, was applied across the entire experiment for that participant.

3.2.4 ***Additional Design Features***

Non-linguistic stimuli such as pure tones and abstract shapes were intentionally chosen to examine implicit-statistical learning effects without the confound of phonological reasoning (sound-to-phoneme-mapping). The current task's non-linguistic nature was designed not only to discourage any labeling of stimuli (for rehearsal) but also to be a fair test of pattern recognition and learning of symbols in general, versus the learning of specifically linguistic material.

Additionally, in the absence of letter stimuli for both of these tasks it was possible to test directly whether adults with reading disorders have problems with implicit-statistical learning of structures at a basic level, beyond exposure to linguistic items.

3.3 Feedback Questionnaire

At the end of both computerized tasks, participants completed a brief questionnaire (See **Appendix A**) about their levels of awareness of the underlying statistical patterns. Only responses to questions that reflected pattern awareness were rated by two independent raters as either *high* or *low* awareness. Agreement ratings were then entered into any main analysis with pattern awareness. Cohen's κ was run to determine degree of inter-rater agreement (Landis & Koch, 1977); there was high agreement between the two rater's judgements ($\kappa = .712$, $p < .001$).

3.4 Normed Behavioral Assessments

Each participant was administered standardized measures of: (1) selected subsections of the Wechsler Individual Achievement Test, 3rd Edition (WIAT-III, Psychological Corp., 2009); and (2) selected subsections of the Wechsler Adult Intelligence Scale 4th Edition (WAIS-IV, Wechsler, 2008). These measures were used as indices of cognitive, spelling and reading ability, in later analyses. Additionally, they also helped to better characterize the sample of participants. A short description of each subtest is provided below.

3.4.1 ***Reading Ability***

The Word Reading and Pseudoword-Decoding subtests measuring Reading ability were administered from the WIAT- III (Psychological Corp., 2009). *Word Reading* was used to measure speed and accuracy of single word reading. The participant was instructed to read an entire list of words out aloud (but is not instructed to read quickly) and their score reflected words read in the first 30secs of reading. *Pseudoword-Decoding* was used to measure speed and accuracy of decoding non-words. The participant was instructed to read an entire list of nonwords out aloud (but was not instructed to read quickly) and their score reflected nonwords read in the first 30secs of reading.

3.4.2 ***Spelling***

The Spelling subtest measuring orthography was also administered from the WIAT- III (Psychological Corp., 2009). This instrument was used to measure written spelling of single sounds and words from dictation. Each participant was instructed to spell dictated words, without erasing. After having listened to a target word followed by the word within the context of a sentence, the participant was asked to write down the word. Their score reflected accurately spelled words.

3.4.3 ***Cognitive Ability***

The Digit Span and Symbol Search subtests measuring Reading ability were administered from the WAIS-IV (Wechsler, 2008).

Digit Span (forward and backward) was used to measure the participant's ability to recall a series of numbers in a specified order. The backward digit span is a commonly used measure of working memory and the forward digit span is typically used to measure verbal short-term memory. Participants heard a numeric sequence and were asked to recall the sequence in the correct order. The longest number of accurately remembered sequences represented the participant's *digit span* or focus. No visual information was presented. *Symbol search* was used to measure the participant's ability to visually scan for items on paper. This subtest was time sensitive and was used to measure processing speed. In this paper and pencil task, the participant was required to quickly scan visual information on the page and make an informed decision about whether target symbols matched other symbol exemplars. This task required sustained focused attention for a total of two minutes.

3.5 Additional assessments

3.5.1 ***The ADHD Checklist (Appendix B.2)***

All participants were rated as per the ADHD Checklist guidelines presented in the manual and could obtain a lowest possible score of 0, indicating a complete lack of ADHD self-reported symptoms. The highest possible score was 16. This is used as a screening and not a diagnostic tool, and within the present context was used only as a means to assess prevalence of baseline ADHD self-reported symptoms.

3.5.2 *The OMSI scale (Appendix B.4)*

The OMSI (Ollen, 2006) is a ten-item online questionnaire used to assess whether a participant was high or low on musical sophistication or musical ability (Hallam & Prince, 2003). Rather than a comprehensive assessment, it is a quick means to index the levels on which participants differed in musical ability (Ollen, 2006).

Table 2 Descriptives for adults [besides ADHD and OMSI measures, all scores are scaled]

	Group			
	Typical		Atypical	
N	36		16	
	Mean	SD	Mean	SD
Reading	105.500	5.516	98.000	10.782
Pseudoword Decoding	97.194	8.510	87.750	14.510
Spelling[2]	111.000	9.770	89.437	20.150
Digit Span	9.166	2.480	8.375	2.250
Symbol Search	9.250	2.480	7.812	2.830
OMSI	126.027	113.53	157.500	141.78
ADHD	4.638	4.300	7.250	4.540

Mann-Whitney (Mann & Whitney, 1947) tests revealed that the groups differed in terms of their scores on reading [$U = 153.500$; $p = .007$], pseudo-word decoding [$U = 158.500$; $p = .01$] and spelling [$U = 86.000$; $p < .001$]. There was also variability across scores obtained from the ADHD checklist [$U = 180.000$; $p = .031$]. However, the two groups did not significantly differ with regards to scores on the digit span subtest [$U = 252.000$; $p = .471$], symbol search subtests [$U = 212.500$; $p = .131$] or the OMSI [$U = 243.000$; $p = .372$].

[2] $N = 35$ due to one outlier that will be excluded from future analyses with spelling scores.

In terms of pattern awareness, results were comparable across groups --- independent raters judged 67% of typical readers (*N* = 36) and 69% of atypical readers (*N* = 16) as having a high level of pattern awareness.

3.6 Electroencephalography Acquisition

For the artificial grammar learning task, ERPs were time-locked to the onset of each symbol sequence at test only. For the probabilistic statistical learning tasks, ERPs were time-locked to the onset of the predictor.

During the SL tasks, electroencephalography (EEG) data were taken from 256 scalp sites using an Electrical Geodesic Inc. (EGI) sensor net (**Figures 3.8 and 3.9**). Electrode impedances were kept below 50 kΩ. The EEG was acquired with a 0.1 to 100 Hz band-pass at 250 Hz with vertex reference and then re-referenced to the average reference of all sensors and low-pass filtered at 30 Hz. All experimental sessions were conducted in a 132 square foot double-walled, soundproof acoustic chamber. To analyze the effect of the cortical topologic, either nine brain regions of interests (ROIs; see **Figure 3.9**) were demarcated as: left (LAn), middle (FRz), and right anterior (RAn); left (LCn), middle (CNz), and right central (RCn); and left (LPo), middle (POz), and right posterior (RPo) regions or six ROIs (as in **Figure 3.8**). This is because, for the AGL tasks, ROIs were defined similarly to that of Silva et al., (2016) wherein electrodes from the central region were distributed equally between left and right regions. Rather than include all nine regions, this division (into six areas) was performed to ensure comparison between current results and Silva et al., (2016), who also used an artificial grammar learning task.

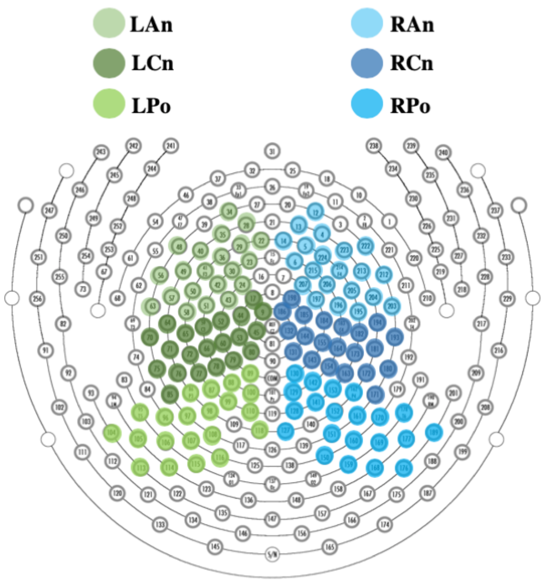


Figure 3.8 Electrical Geodesics Inc. sensor net with six ROIs highlighted for the AGL task

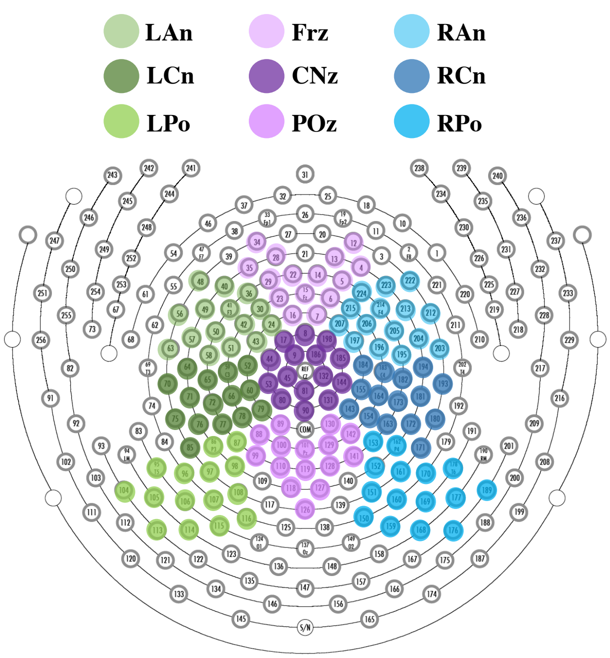


Figure 3.9 Electrical Geodesics Inc. sensor net with nine ROIs highlighted for the visual-motor and auditory-motor learning tasks

4 RESULTS

4.1 Statistical Analyses

Prior to any main analyses, the data were checked for outliers and whether the data followed an approximately normal distribution. All analyses were carried out after meeting basic assumptions of repeated ANOVA[3], t-tests, non-parametric Mann-Whitney U tests and Spearman correlational analyses. Due to the unbalanced sample size between typical and atypical readers, for each task, results are first presented within each group separately. This is followed by non-parametric tests to further investigate for any group differences.

4.1.1 *Artificial Grammar Learning (AGL; Visual)*

Closely following Silva, Folia, Hagoort & Peterson, (2017), behavioral data analyses included a report of accuracy (percent correct) but the main analyses are centered on endorsement rates (proportion of items in a given category that were classified as grammatical, regardless of their actual status). Paired-sample two-tailed t-tests and repeated measures ANOVAs with significance thresholds of .05 were used to analyze the data. Factors for grammaticality were Grammatical (G) vs. Non-Grammatical (NG) and for chunk strength were high (HCS) vs. low (LCS). When collapsed across the factors this resulted in four main categories: GH, GL, NGH, NGL (see methods section for details). Learning based on grammatical status (or increased discrimination between G and NG) and chunk strength-based learning (increased discrimination between HCS and LCS) were both tested via difference scores for behavioral and ERP data.

[3] Statistical analyses include ANOVAs and not ANCOVAs with age/reading ability as covariate. This was because the current data violate one or more ANCOVA assumptions especially with regards to: (a) the presence of (age) outliers, (b) homogeneity of regression slopes and (c) linear relationship between covariate and dependent variable at each level of the independent variable (even after data transformation).

The EEG data from all trials were analyzed by way of repeated-measures ANOVAs. The comparisons of interest were based on the factor's grammatical status (two levels, G vs. NG) and local subsequence familiarity (CS, two levels, HCS and LCS). Based on visual inspection and similar to previous research (Christiansen et al., 2012; Silva et al., 2016) mean voltages were computed at two different time windows of interest (500–700ms and 700–900ms). Electrode clusters resulted in six regions of interest, each comprising twenty-one electrodes (**Figure 3.8** in Methods). This yielded factors such as caudality with three levels (Anterior, Central, Posterior) and laterality with two (Left, Right). When reporting main effects or interactions, Greenhouse-Geisser corrections were applied in cases of non-sphericity (with Bonferroni corrections). Along with grand average waveforms, topological-plot views (at 100ms time window views) generated from difference scores for grammaticality (NG minus G) and chunk strength (LCS-HCS) are also presented below.

To investigate the link between behavioral measures and ERPs and other neuropsychological measures, Spearman's r correlations were computed between: (1) behavioral difference scores from endorsement rates (G-NG and HCS-LCS) and other reading/cognitive outcome measures; and (2) at ROIs chosen a-priori (irrespective of statistically significant differences between conditions) via mean voltage differences for grammaticality (NG-G) and chunk strength (LCS-HCS).

4.1.1.1 ***Behavioral Results***

4.1.1.1.1 Typical

Paired t-tests for these typical adults (N = 22 only; due to one outlier and data loss from technical issues associated with this task) indicated that there was a statistically significant difference in accuracy between correctly classifying an item as G (M = 56.25; SD = 17.190) vs.

NG (M = 41.690; SD = 13.401), t(21) = 2.870; p = .009, with G being slightly above chance compared to NG (**see Figure 4.1,** left panel). Similarly, paired t-tests indicated a statistically significant difference between accurately classifying an item as HCS (M = 45.880; SD = 12.298) vs. LCS (M = 52.059; SD = 10.925), t(21) = -2.313; p = .031, with LCS being marginally above chance compared to HCS. When asked to rate their confidence of responses, participants were most likely to confirm that they were sure of their grammaticality classification (the most frequently selected response was option 4 --- "I am sure", see **Table** in ***Appendix C.1***).

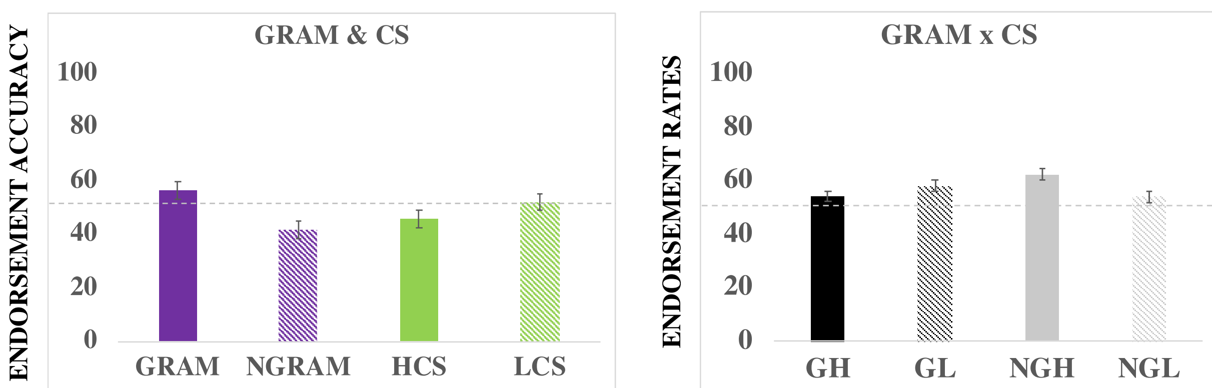


Figure 4.1 Left Panel: Endorsement accuracy for Grammaticality and CS by category; Right panel: Endorsement rates across Grammaticality X CS

Using endorsement rates (See **Figure 4.1,** right panel; irrespective of accuracy, in line with Knowlton & Squire, 1996; Silva et al., 2017) the results from a repeated 2x2 (Grammaticality x chunk strength) ANOVA, revealed no statistically significant main effect of grammaticality F(1,21) = .243; p =.627; η^2 = .011 or CS F(1,21) = .964; p =.337; η^2 = .044. However, there was a significant interaction between Grammaticality and chunk strength, F(1,21) = 5.348; p =.031; η^2 = .203 (**Figure 4.2**). Consistent with previous research (Pavlidou & Williams, 2010) both grammaticality and CS influenced adult learning. Endorsement at test was higher for NG-High compared to NG-Low (similar to baseline for Silva et al., 2017).

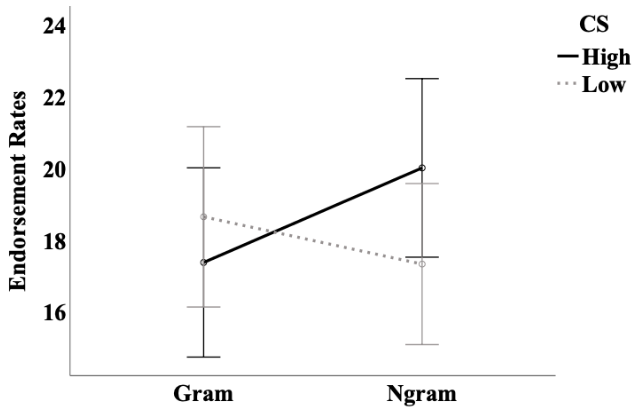


Figure 4.2 Grammaticality by CS interaction for typical readers.

4.1.1.1.2 Atypical

Paired t-tests for atypical adults (*N* = 12 only; due to data loss from technical issues associated with this task) indicated that there was no statistically significant difference in accuracy between correctly classifying an item as G (*M* = 54.687; *SD* = 29.533) vs. NG (*M* = 47.786; *SD* = 28.010), $t(11) = .432$; $p = .674$ (**see Figure 4.3,** left panel). Similarly, paired t-tests did not indicate a statistically significant difference between accurately classifying an item as HCS (*M* = 49.088; *SD* = 8.413) vs. LCS (*M* = 53.385; *SD* = 11.784), $t(11) = -1.127$; $p = .284$. When asked to rate their confidence of responses, participants were most likely to confirm that they were sure of their grammaticality classification (the most frequently selected response was option 4 --- “I am sure”, see **Table** in ***Appendix C.1***).

Repeated-mixed ANOVA with group (atypical readers) revealed no statistically significant main effect of grammaticality $F(1,11) = .595$; $p = .457$; $\eta^2 = .051$ or CS $F(1,11) = .831$; $p = .381$; $\eta^2 = .07$; nor was there a significant interaction between the two factors and group $F(1,11) = 3.152$; $p = .103$; $\eta^2 = .223$.

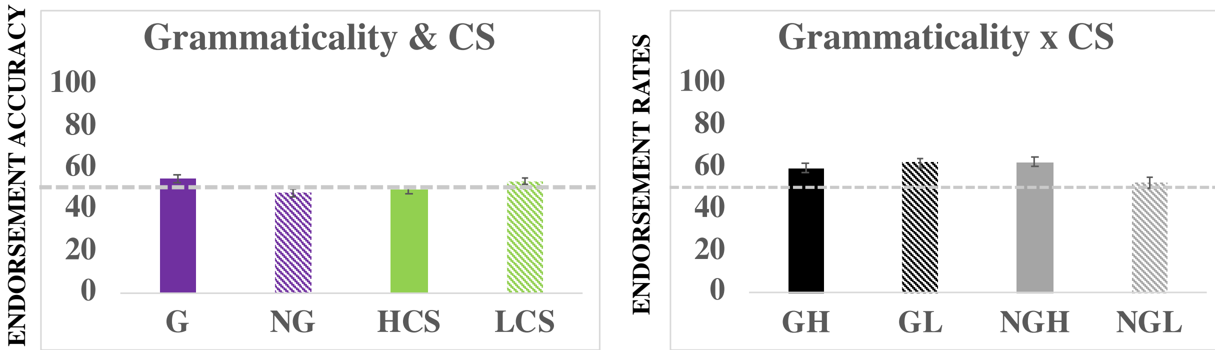


Figure 4.3 Left Panel: Endorsement accuracy for grammaticality (Grammaticality) and chunk strength (CS) by category; Right panel: Endorsement rates across Grammaticality X CS; both bottom panels show atypical reader data.

4.1.1.2 ***Between group non-parametric tests***

To investigate whether the two groups differed on each of the two grammaticality factors (G/ NG) and CS (High/ Low) in terms of endorsement accuracy or endorsement (irrespective of accuracy), non-parametric Mann-Whitney tests were performed. Results are as follows: No significant group differences were found between typical (N = 22) and atypical readers (N = 12) in terms of item endorsement accuracy on whether items were G, (U = 120.000; p = .683); NG (U =93.500; p = .168); HCS (U = 113.500; p = .511) or LCS (U = 112.000; p = .488). Similarly, in terms of item endorsement only, no significant group differences were found whether items were GH (U = 113.000; p = .511); GL (U = 115.000; p = .557); NGH (U = 129.000; p = .929); or NGL (U = 112.000; p = .488).

Table 3 Percentage of participants below chance for endorsement accuracy

	G	NG	HCS	LCS
Typical	41	82	64	55
Atypical	50	42	58	33

Table 3 above shows that the participants differ in terms of learning at chance and that this is not considered in current analyses. Although separating participants into learners who scores above chance vs. those who scored below; as well as accounting for reading ability groups is beyond the scope of this study, this is a learning issue and is addressed in the discussion chapter.

4.1.1.3 ***ERP Results***

4.1.1.3.1 Typical

Visually, grand averages (**Figure 4.4, left panel**) indicated lower amplitudes for GL in the left hemispheres and higher amplitudes for GH in the right. For NGH and NGL amplitudes no particular pattern was observable.

Both time windows showed a main effect for laterality as well as an interaction of chunk strength x laterality. Only the last time window indicated a three-way interaction of grammaticality x caudality x laterality, $F(1.27, 30.485) = 4.448$; $p = .035$; $\eta^2 = .156$, (displayed below in **Figure 4.4, right panel**). This indicates consistently higher amplitudes in the right hemisphere for G compared to NG trials in posterior regions, but was inconsistent between left and right hemispheres for grammatical and non-grammatical sequences in anterior and central regions. Similar to Silva et al., (2016) current results do implicate effects of grammaticality in both time windows.

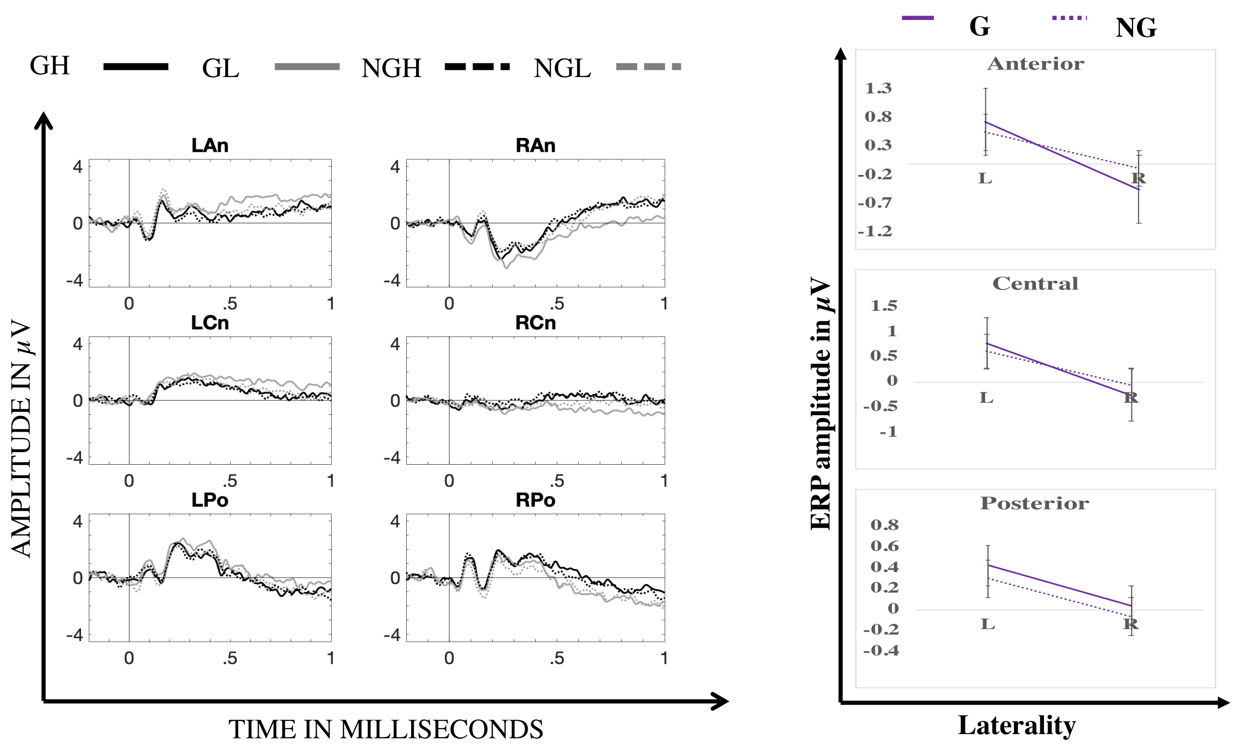


Figure 4.4 Left panel: Grand averages for the AGL task, for typical readers; Right panel: Results of the grammaticality X Caudality X Laterality interaction at 700-900ms

Additionally, findings did reveal main effect for *laterality* across both time windows: (i) **500–700ms** [F(1,24 = 13.778; p=.001; η^2 = .356] and (ii) **700–900ms** [F(1,24 = 9.104; p=.006; η^2 = .275]. On average, amplitudes were higher for left compared to right hemispheres.

Similarly, both time windows showed chunk strength x laterality interactions: (i) **500–700ms** [F(1,24 = 18.017; $p < .001$; η^2 = .429] and (iv) **700–900ms** [F(1,24 = 18.916; $p <.001$; η^2 = .441]. Pairwise comparisons indicated that amplitudes across the windows were always higher for low compared to high CS and were also higher for left compared to right hemispheres

The topological views below (**Figure 4.5**) indicate greater amplitude differences in terms of grammaticality in right brain regions that builds up over time. Additionally, consistently greater CS amplitude differences in left brain regions were observed for typical readers.

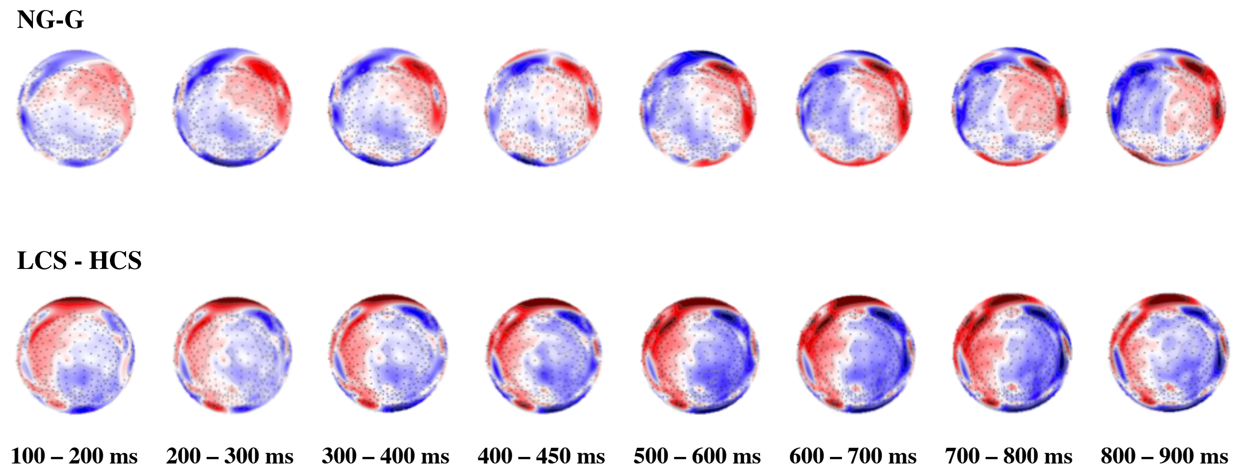


Figure 4.5 Topological views for the grammaticality and CS difference scores over each time window, for typical readers.

4.1.1.3.2 Atypical

Visual inspection (**Figure 4.6**) revealed that the atypical group produced relatively lower amplitudes for GH and NGH in the left hemispheres and higher amplitudes in the right. In contrast, compared to GL and NGL amplitudes appeared lower in the right and higher in the left, especially in anterior regions. Visually, thy atypical readers' waveforms showed a pattern similar to the typical readers.

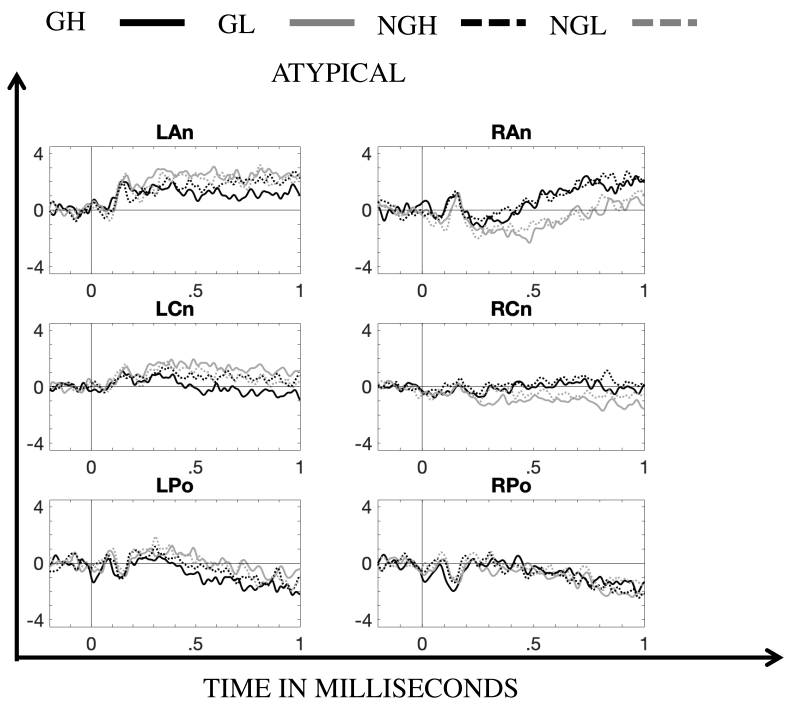


Figure 4.6 Grand averages across ERPs for grammaticality and CS for atypical readers in the AGL task

For the atypical readers, both time windows showed a main effect for laterality as well as an interaction of chunk strength x laterality x caudality. Results of the repeated measures ANOVAs are presented below. Both, the 500-700ms: $F(1.254, 13.793)=12.746$, $p = .002$, $\eta^2 = .537$, as well as the 700-900ms time window: $F(1.269, 13.962)=13.397$, $p = .002$, $\eta^2 = .549$ --- showed a significant interaction for chunk strength x laterality x caudality. This is depicted in **Figure 4.7** below. Across both time windows, amplitude differences were observable in anterior regions (more so than central and posterior) were right lateralized.

Main effect for *laterality* was found across both windows: (i) **500–700ms** [F(1,11 = 9.735; p=.010; $\eta^2 = .469$] and (ii) **700–900ms** [F(1,11 = 7.361; p=.020; $\eta^2 = .401$].

Both time windows also showed a chunk strength x laterality interaction: (i) **500–700ms** [$F(1, 11)= 5.126$; $p =.045$; $\eta^2 = .318$] and (ii) **700–900ms** [$F(1, 11) = 5.193$; $p = .044$; $\eta^2 = .321$].

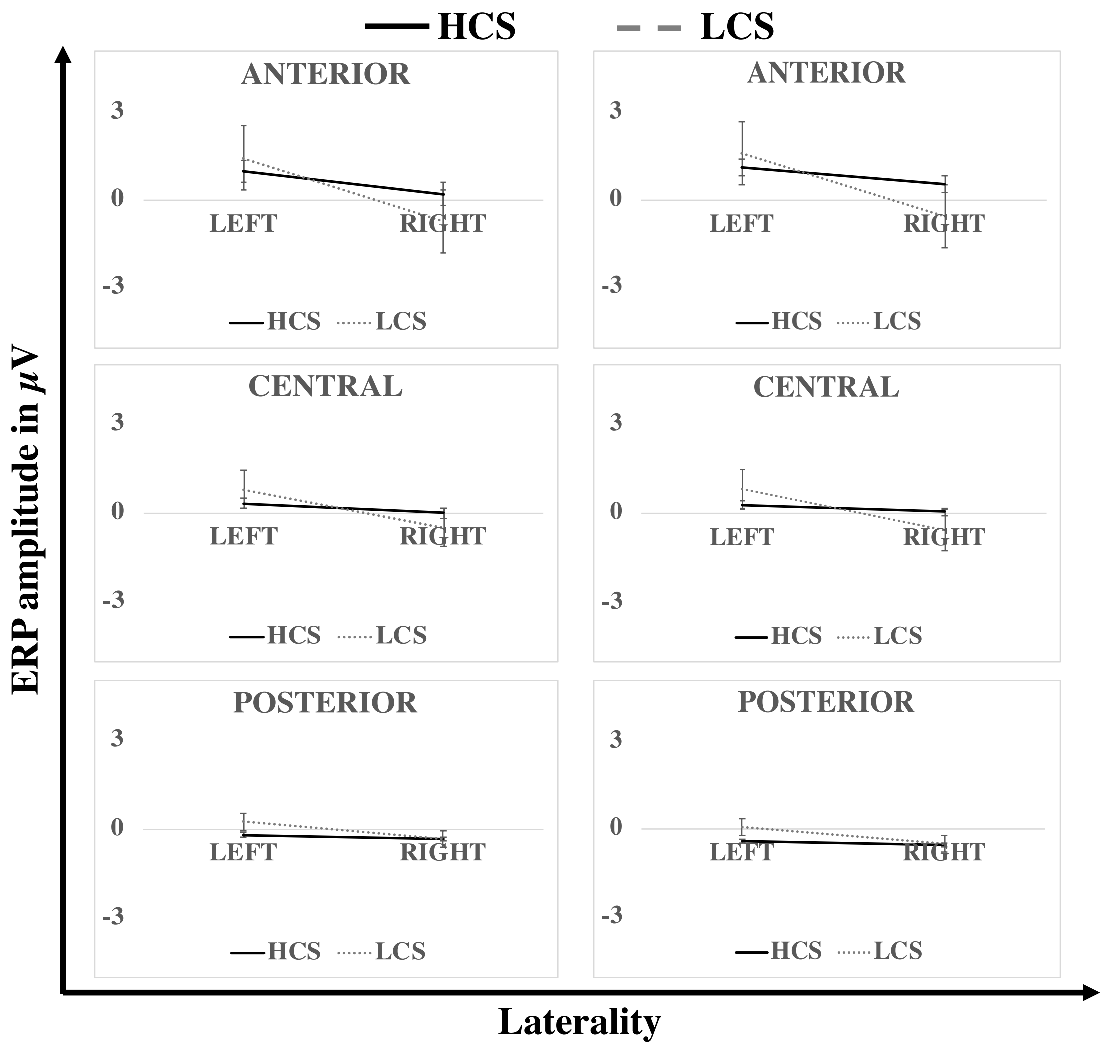


Figure 4.7 Interaction with caudality, laterality and CS for the AGL task for atypical reader; left panel: within 500 – 700ms and right panel: within 700 – 900ms.

Figure 4.9 below captures the amplitude differences for grammaticality and CS across matched groups. Topological plots for grammaticality appear comparable across groups, but for CS, the typical group shows a greater amplitude difference at early left anterior regions compared to atypical readers. Instead, atypical readers' topological plots show greater amplitude differences over all time windows for CS in left posterior regions.

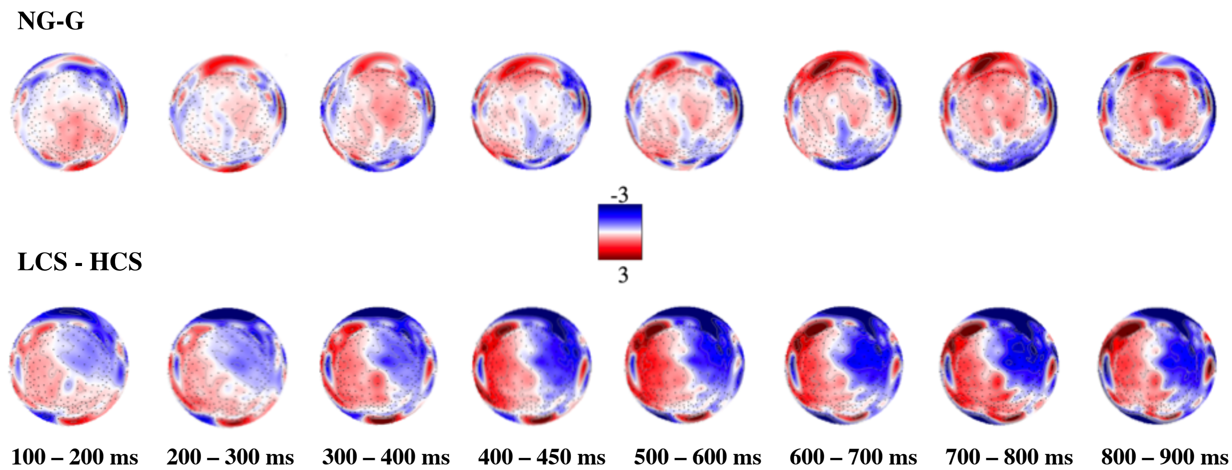


Figure 4.8 Topological views for the grammaticality and CS difference scores over each time window, for atypical readers.

4.1.1.4 *Between group non-parametric tests*

To investigate whether the two groups differed on endorsement for each of the two grammaticality factors (G/ NG) and CS (High/ Low) in terms of ERP amplitudes, non-parametric Mann-Whitney tests were performed only in the LPo region in both time windows (based on ANOVA findings, above). Results between typical (N = 25) and atypical readers (N = 12) are as follows: (i) **500-700ms** - GH (U = 79.000; p = .021); GL (U = 101.000; p = .117); NGH (U = 90.000; p = .053); or NGL (U = 137.000; p = .689); (ii) **700 – 900ms** - GH (U = 88.000; p = .045); GL (U = 115.000; p = .267); NGH (U = 103.000; p = .133); or NGL (U = 144.000; p = .860).

Thus, in the first time window, the groups differed only in terms of GH and NGH item endorsement; and in the second time window, group differences were only observed for GH items.

4.1.1.5 *Correlations*

Spearman's r_s correlation coefficients were computed between: (1) behavioral difference scores from endorsement rates (G-NG and HCS-LCS) and outcome measures (raw scores on Reading, Pseudoword decoding, spelling, digit span, symbol search, OMSI and pattern awareness scores); and (2) at ROIs (left and right, for anterior as well as posterior regions) mean voltage differences (chosen based on visual inspection and are similar to exploratory analyses in Silva et al., (2017)] for grammaticality (NG-G) and chunk strength (LCS-HCS). Age was also entered to check for its potential influence in the between-groups analysis. Only correlations with the AGL/SL tasks for which p <.001 are discussed below; but all correlations are presented in ***Appendix C.1***.

No statistically significant (p <.001) correlations with the AGL tasks were found for typical readers. All correlation tables are presented in ***Appendix C.1***. Atypical reader results showed that scores on symbol search were positively correlated with AGL scores (NG-G) at RPo regions, only during the 500-700ms time window --- (N = 12, r_s =.711, p <.001).

4.1.2 ***Probabilistic Statistical Learning Task (Visual-motor)***

Both behavioral and ERP data were analyzed in a way similar to Jost et al., (2015). Behavioral data analyses included mean RTs for HP and LP conditions over the 2 phases within the task. Phase 2 was split into a first and second half, each half comprised of 3 blocks of trials, to track learning over the task. Thus, factors for predictability were (HP vs. LP), and for phase (1/2a/2b). *Learning effects* or learning based on predictability conditions (increased discrimination between HP and LP) across the phases was the main outcome of interest across behavioral and ERP findings. This is also referred to as transition-timing (Dehaene et al., 2015).

The ERP data from all trials were analyzed using repeated-measures ANOVAs. The comparisons of interest were based on predictability (two levels, HP vs. LP) and phase (1/2a/2b). Following Jost et al. (2015), mean voltages were compared at 400–700ms and nine regions of interest were computed, each comprising fifteen electrodes (**Figure 3.9**). Caudality entered the analysis with three levels (Anterior, Central, Posterior) and laterality with three as well (Left, Middle, Right). Main effects of phase and predictability were reported with Greenhouse-Geisser corrections in case of non-sphericity (with Bonferroni corrections). Along with grand average waveforms, topological-plot views generated from difference scores for predictability (HP-LP) and are also presented below.

To investigate the link between ERPs and behavioral decision as well as ERPs and other neuropsychological measures, Spearman's r_s correlations were computed between: (1) behavioral difference scores from mean RTs (LP - HP) and other reading/ cognitive outcome measures; and (2) at ROIs containing mean voltage differences (HP vs. LP).

4.1.2.1.1 Typical

A repeated measures ANOVA was used to investigate whether there were statistically significant differences across average RTs by phase and predictability condition with the typical readers only. This is depicted in the left panel of **Figure 4.10**, showing the average RTs across phases.

Results of the ANOVA revealed a significant main effect of predictability, F(1,33=11.035, p =.002, η^2 = .251, but not phase, F(1,66)=.570, p =.515, η^2 = .017. There was a statistically significant interaction between phase and predictability, F(2,66)=1.629, p =.204, η^2 = .047 (see **Figure 4.10**, right panel). In typical readers, across the phases, the expected learning effect (RTs for LP > HP) was observed.

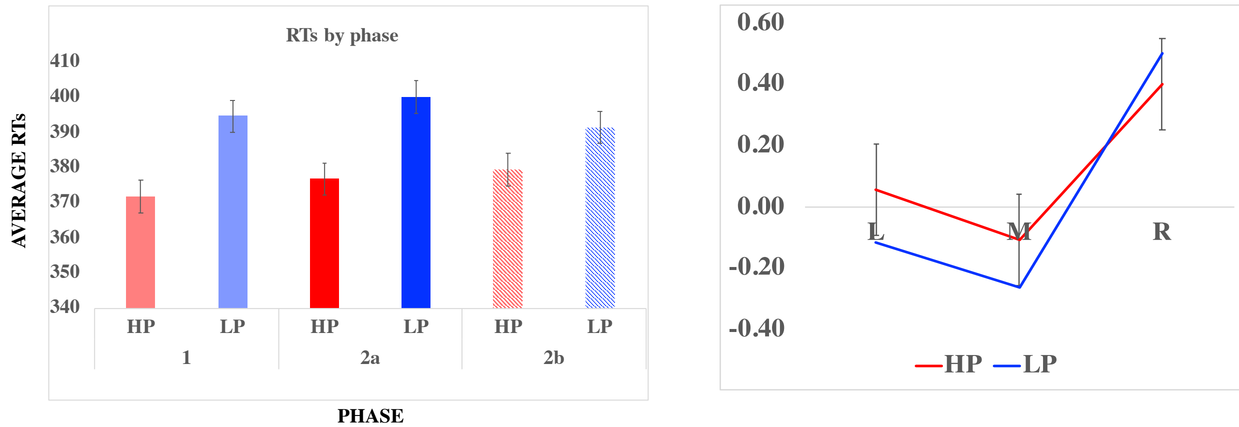


Figure 4.9 Left: Average RTs by predictability over each phase: Right: interaction between predictability and laterality --- for typical readers

4.1.2.1.2 Atypical

Similarly, a repeated measures ANOVA was used to investigate whether there were statistically significant differences across average RTs by phase and predictability condition across atypical readers. The results are depicted in **Figure 4.11**. There was a significant main effect of predictability, F(1,11=16.066, p =.002, η^2 = .594, main effect of phase was right at significance F(1.611,17.721) = 3.753, p =.052, η^2 = .254; but no significant phase x predictability interaction was observed F(1.169, 12.86) =2.466, p =.138, η^2 = .183, as was the case for typical readers.

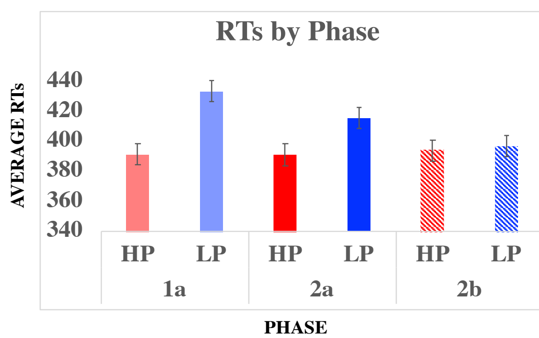


Figure 4.10 Average RTs, in ms, by predictability over each phase for atypical readers

4.1.2.2 *Between group non-parametric tests*

To investigate whether the two groups differed in terms of RTs within predictability condition (HP/ LP) across each phase (1/ 2a/ 2b), non-parametric Mann-Whitney tests were performed. Results are as follows: significant RT group differences were found between typical ($N = 34$) and atypical readers ($N = 12$) only for the LP condition at Phase 1, ($U = 96.000$; $p = .007$); but not for any other phases and predictability conditions. Non-significant results were as follows: Phase 1-HP, ($U = 167.500$; $p = .361$); Phase 2a-HP ($U = 170.000$; $p = .395$) and LP ($U = 150.000$; $p = .177$); Phase 2b-HP ($U = 165.000$; $p = .329$) and LP ($U = 198.500$; $p = .891$).

4.1.2.3 *ERP Results*

4.1.2.3.1 Typical

Visual inspection of the ERP waveforms (**Figure 4.12**; left panel) for the typical group indicate the presence of the typical learning effect (higher amplitudes for HP compared to LP) in Phase 1, where the statistical probability between predictor-target was either 90% or 10%. This difference is especially clear in the centro-posterior region/POz (Jost et al., 2015) within ~400-700ms. This effect remains throughout both phases but lessens in amplitude difference and latency in Phase 2 within ~500-600ms, which would be in line with the task demands (switch to 50-50% predictor-target relationship). Additionally, amplitudes for HP (vs. LP) seem to be higher for left and central compared to right cortical regions.

Similarly, topological-plots (**Figure 4.12**; right panel) show higher posterior amplitude differences across phases. Visually, this difference seems to decrease in Phase 2b ~ 500-600ms.

Using a repeated ANOVA, with ERPs as dependent variable, findings showed that there was a main effect for predictability [$F(1,33)=5.279$; $p=.028$; $\eta^2 =.138$], laterality [$F(1.770,58.423)=16.751$; $p<.001$; $\eta^2 =.337$] and caudality [$F(.109, 35.959)=25.928$; $p<.001$; η^2

=.440] as well as a predictability x laterality interaction [F(1.856, 61.242) = 7.445; p=.002; η^2 =.184] in the 400-700ms time window. This was indicative of higher amplitudes for HP (compared to LP) in left and central ROIs but not for the right hemispheres.

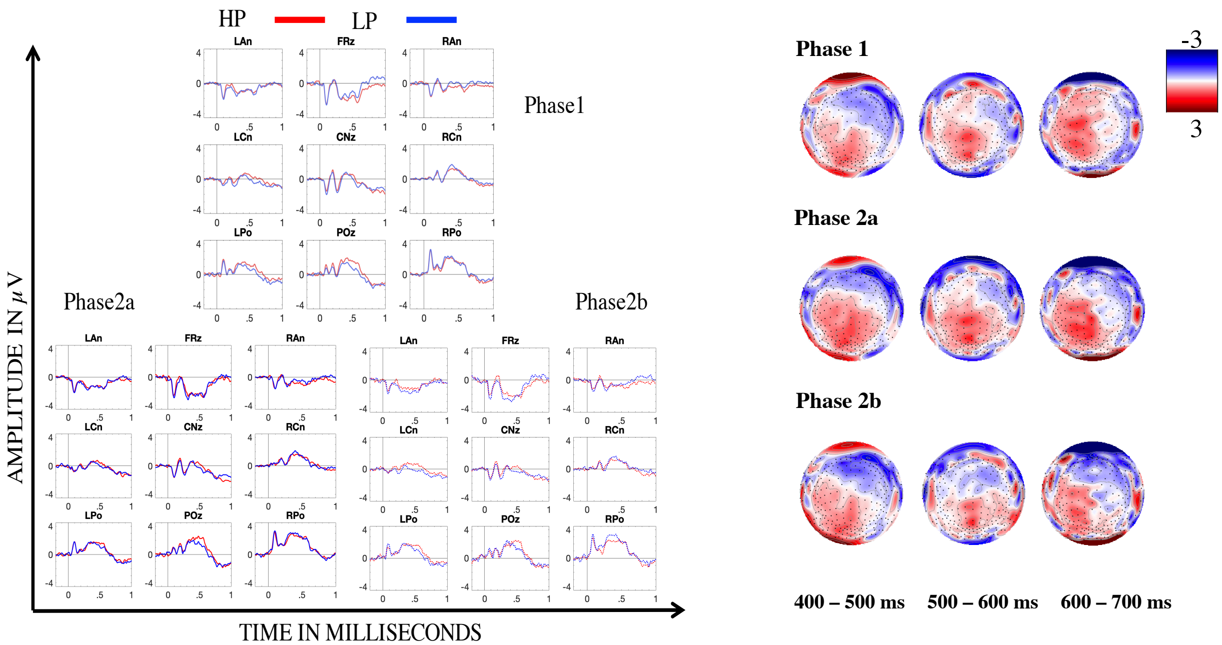


Figure 4.11 Grand averages for each predictability condition over the three task phases; Right: Topological views of the difference scores (HP – LP) for each phase ---for typical readers in the 400-700ms time window

4.1.2.3.2 Atypical

Visual inspection of grand averages in **Figure 4.13** for matched-typical readers reveals the same pattern as previously mentioned for the typical readers. However, atypical readers do not show a distinct HP > LP difference in any of the phases, especially not at POz. This is (visually) indicative of atypical learning of the predictor-target contingencies in this task.

Result of a repeated ANOVA indicated that for atypical readers there was only a significant main effect for phase [F(1.79, 25.057)=3.373; p=.055; η^2 =.194]. No further main effects or significant interactions were observed.

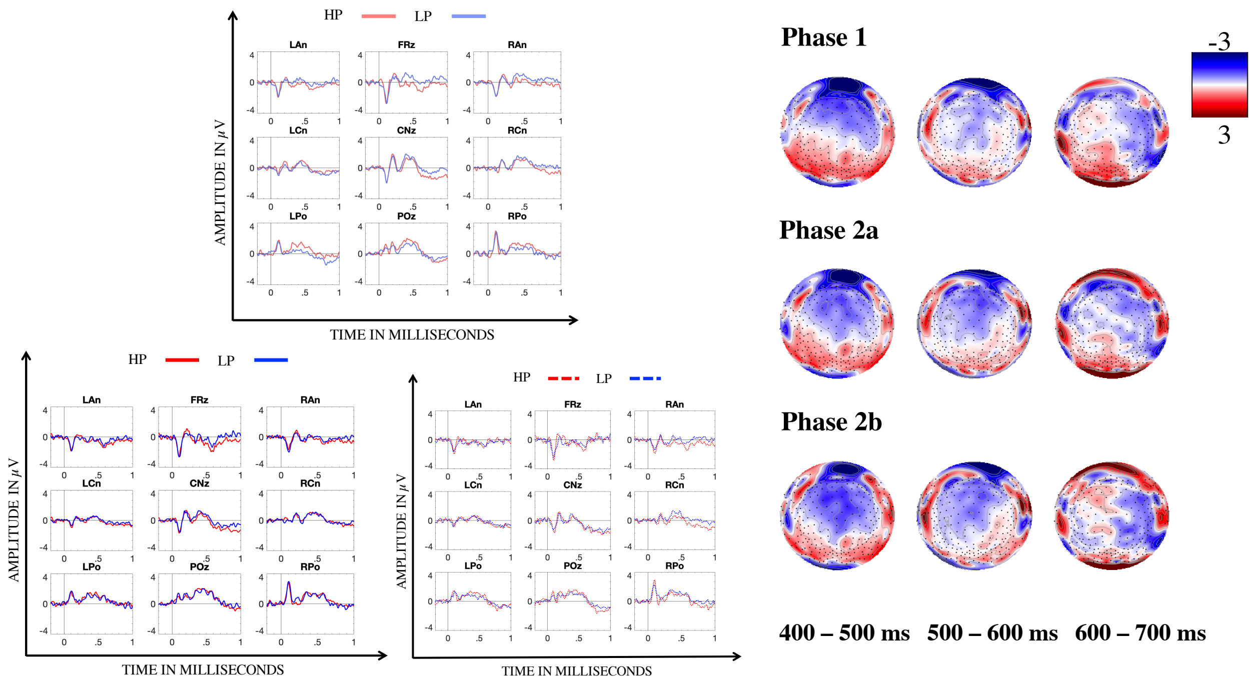


Figure 4.12 Grand averages for each predictability condition over the three task phases; Right: Topological views of the difference scores (HP – LP) for each phase ---for atypical readers in the 400-700ms time window

Similar to the waveforms, the topological-plots depicted in **Figure 4.13** show that amplitude differences were generally greater for the typical readers at Phase 1. Whereas atypical reader topological-plots show little change in amplitude difference by phase, the typical readers show overall greater amplitude differences at posterior areas, which was reduced between Phase 2a and 2b and might be reflective of learning the predictability condition switch (from 90-10% to 50-50% predictor-target rule).

4.1.2.4 *Between group non-parametric tests*

To investigate whether the two groups differed in terms of ERP amplitude at POz only, within 400-700ms, across predictability condition (HP/ LP) and for each phase (1/ 2a/ 2b), non-parametric Mann-Whitney U tests were performed. Statistically non-significant results are as follows: No significant group differences at POz were found between typical ($N = 34$) and atypical readers (N = 15) for Phase 1 HP, (U = 248.000; p = .879) or LP (U = 239.000; p = .729); Phase 2a-HP, (U = 248.000; p = .879) or LP (U = 198.000; p = .216); Phase 2b-HP (U = 243.000; p = .795) or LP (U = 208.000; p = .308).

4.1.2.5 ***Correlations***

No statistically significant (p <.001) correlations with the visual probabilistic task were found for typical readers. All correlation tables are presented in ***Appendix C.2***.

4.1.3 ***Probabilistic Statistical Learning Task (Auditory-motor)***

Analyses were carried out in line with the visual-motor learning task above but with a smaller time-window of 500-700ms (based on visual inspection of the grand averages), yet is still similar to the analyses of Jost et al. (2015). For the behavioral RTs, Phase 1 did not yield sufficient data and was hence dropped from the analyses[4]. All ANOVA results are Greenhouse-Geisser corrected with Bonferroni adjustments.

4.1.3.1.1 Typical

Average RTs were first compared within typical readers only, to investigate whether there were statistically significant differences across average RTs by phase and predictability condition. Average RTs by phase and predictability are depicted in **Figure 4.15** below. A repeated measures ANOVA with mean RTs as dependent variable and within factors of predictability (HP/LP) and phase (only phase 2a vs. phase 2b) revealed statistically significant main effects for phase. $F(1,23)=.150$; $p=.702$; $\eta^2=.006$, but nonsignificant main effect for predictability, $F(1,23)=3.549$;

[4] The lack of behavioral data stemmed from the fact that a majority of participants either did not respond accurately in the LP condition or their responses were not recorded because they were longer than 500ms. For this reason, it was impossible to compare HP and LP RTs at Phase 1.

p=.072; η^2 =.134. There was no statistically significant interaction between phase x predictability, $F(1,23)$=.937; p=.343; η^2 =.039, as was the case in the visual-motor task.

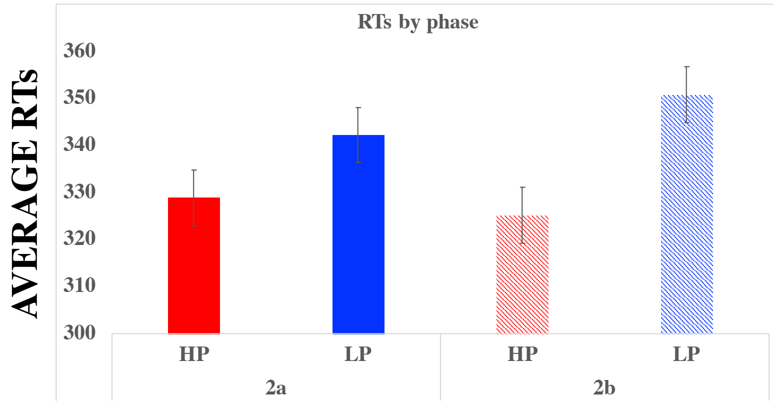


Figure 4.13Average RTs by predictability and task phase for the typical readers.

4.1.3.1.2 Atypical

Similar to the typical reader analyses, a repeated measures ANOVA for the atypical readers with mean RTs as dependent variable and within factors of predictability (HP/LP) and phase (only Phase 2a vs. Phase 2b) did not reveal statistically significant main effects for predictability [$F(1, 9)$=.003; p=.960; η^2 =.000] or phase [$F(1, 9)$=.001; p=.979; η^2 =.000]; nor was there a statistically significant interaction between phase x predictability [$F(1, 9)$=.131; p=.725; η^2 =.014]. Average RT's across groups are depicted below in **Figure 4.16**.

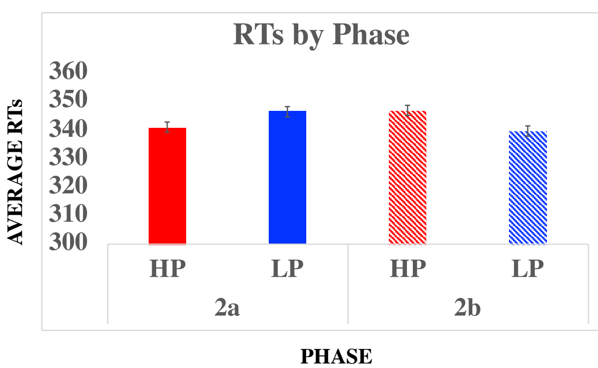


Figure 4.14 Average RTs (in ms) by predictability and task phase for the atypical readers

4.1.3.2 *ERP Results*

4.1.3.2.1 Typical

Visual inspection of ERP waveforms presented in **Figure 4.17** (left panel) did not indicate clear amplitude differences across phases. Additionally, waveforms reflect a barely observable POz amplitude difference. Topological views show greater HP-LP amplitude differences in anterior-central regions for Phase 1 and 2a but then shift to posterior regions in Phase 2b.

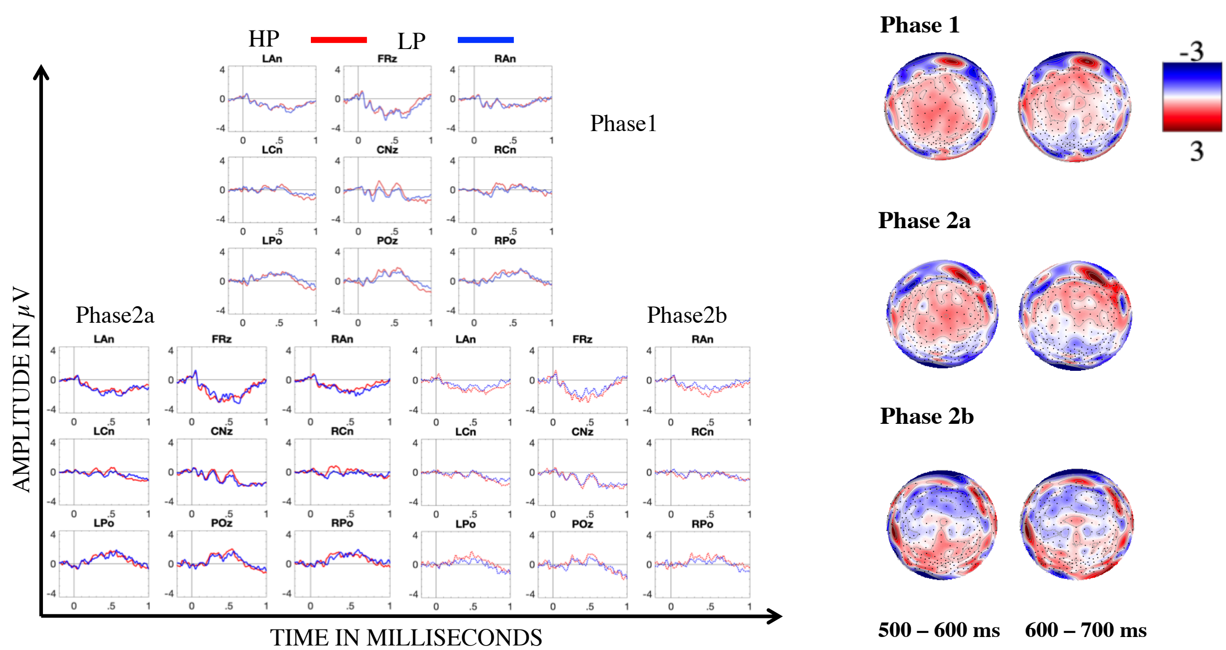


Figure 4.15 Grand averages by predictability condition for each task phase; Right: Topological views of the difference scores (HP-LP) for each phase during the 500-700ms time window – for typical readers.

ERP results for the 500 – 700ms time window showed a main effect for phase [$F(1.442,41.832)=10.862$; $p = .001$; $\eta2 = .272$], predictability [$F(1,29)=6.668$; $p = .015$; $\eta2 = .187$], laterality [$F(1.659,48.122)=3.506$; $p = .046$; $\eta2 = .108$] and caudality [$F(1.199,34.785)=26.610$; $p < .001$; $\eta2 = .479$] as well as a phase x predictability interaction, shown in **Figure 4.16**,

[$F(1.397,40.515)=12.180$; $p<.001$; $\eta^2=.296$] and a phase x caudality interaction [$F(2.11,61.189)=4.266$; $p=.017$; $\eta^2=.128$].

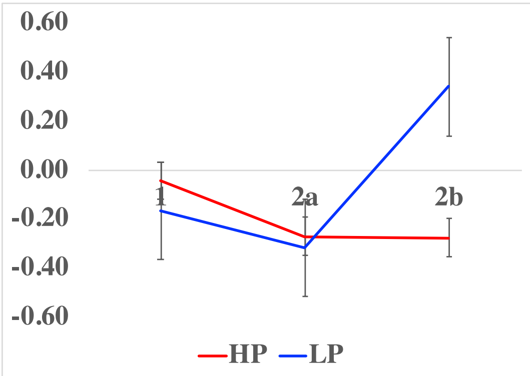


Figure 4.16 Interaction between predictability condition and phase for typical readers

The interaction above shows that in Phase 1 and Phase 2a, HP amplitudes were higher than LP but the reverse occurs in Phase 2b. This could be partly due to learning of the switch in probability that target saliency is transferred to LP from HP over time.

4.1.3.2.2 Atypical

Visual inspection of grand averages (depicted in **Figure 4.17,** below) showed higher LP compared to HP amplitudes in anterior and central regions at Phase 2a. Phase 2b amplitudes at POz reflect higher LP compared to HP amplitude. Visually, topological-views (**Figure 4.17**; right) indicate that atypical readers show higher amplitudes for LP that increase overtime in Phase 2 and have an anterior-posterior shift, whereas the typical readers show the opposite pattern.

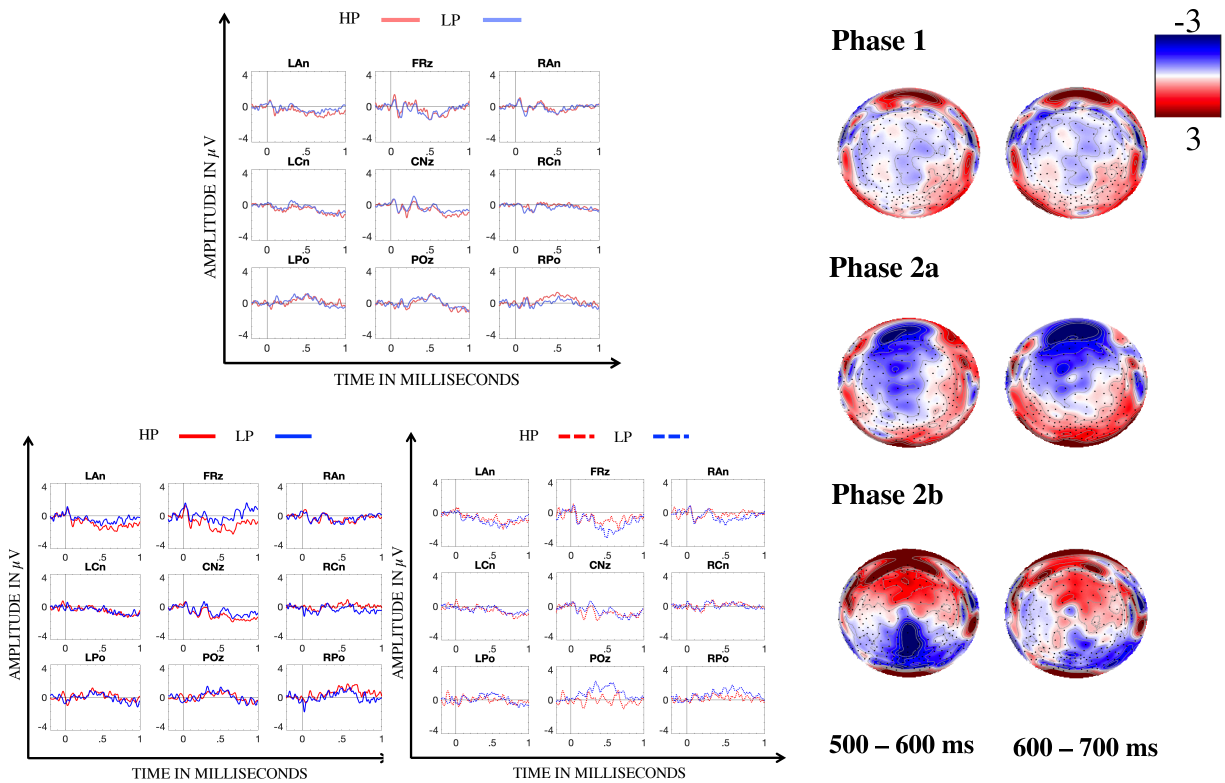


Figure 4.17 Left: Grand averages by predictability condition for each task phase; Right: Topological views of the difference scores (HP-LP) for each phase during the 500-700ms time window – for atypical readers.

A repeated ANOVA with ERP waveforms as dependent variable, for the atypical readers, within the 500 – 700ms time window revealed no significant main effects or interactions. Results for predictability and phase are as follows: predictability, $F(1,14)=1.493$; $p=.242$; $\eta^2=.096$; phase, $F(1.459, 20.432)=.76$; $p=.442$; $\eta^2=.051$; predictability x phase $F(1.757,24.599)=.301$; $p=.715$; $\eta^2=.021$.

4.1.3.3 ***Between group non-parametric tests***

To investigate whether the two groups differed in terms of ERP amplitudes between 500-700ms at POz, across predictability condition (HP/ LP) across each phase (2a/ 2b), non-parametric Mann-Whitney tests were performed. Results are as follows: a significant group difference was found between typical (N = 30) and atypical readers (N = 15) for Phase 1 HP only (U = 135.000; p = .030) but not for LP (U = 195.000; p = .470). Additional (non-significant) group differences were observed for: Phase 2a HP, (U = 185.000; p = .336); LP (U = 211.000; p = .736); Phase 2b-HP, (U = 217.000; p = .8470) and LP (U = 216.000; p = .828).

4.1.3.4 ***Correlations***

No statistically significant (p <.001) correlations with the auditory probabilistic task were found. All non-significant correlation tables are presented in ***Appendix C.3.***

5 DISCUSSION

4.2 General Overview

The present study was designed to investigate different types of implicit-statistical learning in atypical readers. Using both RTs and ERP recordings, and two commonly used learning paradigms from the literature, it was anticipated that three basic variables could be used to assess learning. In sync with the literature, these variables were operationalized as *grammaticality*, *chunk strength* and *predictability*. However, consistent with Dehaene et al. (2015), information acquired during implicit-statistical learning involves more than what each of the variable names imply. Based on Dehaene et al.'s (2015) theoretical framework, additional underlying mechanisms also apply, including ordinal knowledge, algebraic patterns, chunking and transition-timing. The first two mechanisms pertain to *grammaticality*, chunking is connected to *chunk strength,* information and transition-timing knowledge is thought to underlie the transitional probabilities, predictive sequences or regularities encountered in SRT or other similar probabilistic learning tasks, which in the present context is termed *predictability.*

The first aim of the current study was to examine whether adults diagnosed with a reading disorder showed an implicit-statistical learning deficit via RTs, accuracy endorsement and ERPs in an artificial grammar as well as visual-motor and auditory-motor SL paradigms using non-linguistic stimuli. Overall, behavioral results show comparable performance across groups for all task paradigms. In contrast, the ERP results indicated statistically significant group differences only for the artificial learning and auditory tasks. In addition, (visual) differences were also observable, such as overall longer RTs for the atypical readers. Group differences on the probabilistic/transition-timing based tasks might additionally have yielded statistical significance, were it not for the reduced sample size for (atypical) adults.

The second aim was to examine whether any deficit was specific to the type of learning (i.e., grammaticality, knowledge of chunk strength or predictability) occurring in each task. A deficit, per se was not observable for any of the paradigms, although subtle waveform differences were observable across groups for each task. These differences are interpreted ahead for each task, especially when accuracy, for example, was at chance for one or both groups. Also, discussed are instances where learning was incongruent between behavioral and ERP findings.

The third goal was to examine whether statistical learning ability was correlated with reading, spelling and cognitive ability scores from normed behavioral assessments. Only atypical reader waveform differences for grammaticality were found to be correlated with scores on cognitive ability. A more thorough explanation for this is discussed later.

The fourth objective was to determine whether an observable learning deficit was more pronounced in any one modality. This is still unclear from the current results, mainly because only the probabilistic tasks (not the artificial grammar task) were tested in two modalities; that is, the visual domain was tested via each task paradigm, but the auditory modality only in the SL task. Interestingly, results (or lack of them) from the auditory-motor probabilistic task suggested that task difficulty might have been higher for this task. One justification for this conclusion is that participants might not have being paying attention to the input for some reason, or could not discriminate between the different sounds. According to self-report, approximately 8% of adults rated the visual-motor SL task as difficult, compared to 33% who found the AGL task to be the hardest but 52% rated the auditory-motor SL task as the hardest task.

The fifth aim was to examine whether statistical learning ability depends on awareness of the underlying patterns. It was found that the degree of implicit-statistical learning did not differ much across groups, at least after the fact. This issue is further discussed in the section on limitations.

In sum, although the current results show minor differences across the groups, they are still informative. The study findings above are discussed by task (below), especially in terms of discrepancies between the behavioral and neural correlates of learning.

4.3 Artificial Grammar Learning

Overall, behavioral endorsement accuracy as well as endorsement alone for both typical and atypical readers show similar patterns, in that, they both reflect learning ‘at chance levels’ or slightly ‘above/ below chance’.

One discrepancy between each within-group analysis was that, in terms of accuracy, the average typical reader’s ability favored grammatical over nongrammatical items (Knowlton & Squire, 1996, Pavlidou et al., 2014) but this was not reliably found amongst atypical readers.

Additionally, with regards to endorsements (irrespective of accuracy), current results for non-grammatical items (similar to Silva et al., 2016) were indicative of (i) a preference for high (compared to low) CS within non-grammatical, but (ii) low (compared to high) CS within grammatical items. The former finding is the more expected outcome because it is in line with previous research (see Cleeremans, Destrebecqz & Boyer, 1998) where participants were more likely to exploit fragment-based chunking and therefore more likely to endorse high CS over low CS non-grammatical items. The latter result was more surprising but not critical because grammatical items were consistently endorsed above chance level and did not differ significantly based on level of chunk strength. Thus, this shows that discriminating between CS was more important for non-grammatical than for grammatical items for typical readers. Within the atypical readers, this statistically significant difference amongst endorsement is less apparent, possibly due to the lower sample size. However, no reliable group differences were observed for behavioral data.

Visually, typical and atypical reader ERP waveforms shared similar patterns. According to the findings, typical readers showed a topological difference in response to grammatical vs. non-grammatical items in the final time window. Atypical reader waveforms on the other hand, revealed topological differences in amplitude in response to high vs. low CS items across both time windows. The only reliable group difference was for both grammatical and non-grammatical HCS items in the initial time window and for grammatical HCS items in the final time-window.

Thus, within the AGL task, behavioral data show learning at chance for both groups, indicating that not all participants may have learned to leverage grammatical or CS knowledge while endorsing an item between training and test. This is addressed in the section on limitations. Additionally, although behavioral data were comparable across groups, ERP amplitudes show a connection with grammaticality for typical readers and a connection with CS for atypical readers. Overall, both groups showed amplitude differences for GH and NGH items but this effect persisted for GH items over time. In sum, currently a learning deficit can be ruled out but learning differences across groups may become more apparent with a larger sample size for both groups.

4.4 Probabilistic Learning (Visual-motor)

Typical readers showed learning (i.e., quicker RTs to HP compared to LP) in the visual-motor probabilistic learning task, in line with Jost et al. (2015). This learning effect of predictability remained statistically significant throughout all phases of the task. However, it was expected that the RTs in Phase 2a and 2b would change from Phase 1 to better reflect the *predictability switch* (from 90-10% to 50-50% predictability in task conditions) – at least in terms of direction of RTs. This might have been reflected by comparable LP and HP RTs, but instead it was observed that LP was continually greater than HP. One possible explanation for this unexpected but persistent effect over phases is that after exposure to HP in Phase1, participants may have retained the benefit of consistently quicker RTs to HP, well into Phase 2 even when predictability conditions switched.

Atypical readers did have larger RTs overall, irrespective of predictability condition, which appeared to attenuate over time (although there was no statistically significant group difference by phase or condition). These findings are consistent with literature indicating a general temporal processing deficit for those with reading difficulty (Conlon et al., 2011), meaning individuals with reading/learning impairments would respond at a slower rate to stimuli in a serial visual presentation.

Behavioral group differences were found only for the LP condition at Phase 1 indicating again that atypical readers had longer RTs than typical readers. However, in terms of learning in Phase 1, both groups were comparable.

For the ERP results it was expected, based on Jost et al. (2015), that typical readers would show relatively higher amplitudes for HP compared to LP in Phase1, especially in posterior regions. This would be followed by a statistically significant change by phase and predictability, as a result of having learned the predictability switch (i.e., HP ~ = LPs in RTs and in ERP amplitudes). The Jost et al. (2015) result was also observed in a subsequent study (Singh et al., 2018) that compared children with and without dyslexia on a visual (non-linguistic) statistical learning task with unequal probabilistic predictability conditions throughout the task (akin to the current Phase 1 only; but no Phase 2 switch to equal predictability conditions). The study showed that although behavioral RTs reflected intact learning, children with dyslexia had atypical ERP waveforms suggestive of impaired (or altered) learning of the HP-LP-target rule (as in Phase 1 in the current experiment).

In line with the hypothesized learning effect and Jost et al. (2015), current ERP results revealed that typical reader's waveforms were characterized by relatively higher amplitudes for HP compared to LP in left and central brain regions. However, amplitude difference did not change reliably for predictability and phase across groups. Thus, there is only visual evidence that learning of the predictability condition at Phase 1 and the switch to equal probability in Phase 2 occurred for typical readers. This same pattern of learning by typical readers between Phase 1 and 2 was visually reflected via the higher amplitudes in posterior regions for HP (vs. LP) in Phase 1 but slowly attenuates across the three phases. Although present, this trend is less obvious for the atypical readers. However, there is no support for such learning (at central-posterior sites) in terms of significance tests.

To sum up, the behavioral results did not reliably differ by predictability conditions, but RTs were much slower overall for the atypical readers. Thus, longer RTs indicate might slower learning for atypical compared to typical readers. Additionally, current ERP results did reveal group differences across phases, which rules out a visual statistical learning deficit, per se. However, with a balanced sample size it would be easier to clarify whether learning of the HP-LP target rule at Phase 1 was intact for atypical readers. Currently this learning effect was only observed for typical readers but not for atypical readers, suggesting a possible learning discrepancy.

4.5 Probabilistic Learning (Auditory-Motor)

A difficulty with the behavioral data in this task resulted from the fact that a majority of participants either did not respond accurately in the LP condition or their response was not recorded because it was longer than 500ms, resulting in less RT data being retained. For this reason, it was not only impossible to get an estimate of RT performance (HP vs. LP) within Phase 1, but also comparing Phase 2 performance with Phase 1 was not an option.

Overall, RTs of typical readers reflected the learning effect (HP < LP) in Phase 2, similar to the visual task above and no statistically significant difference was observed for predictability conditions between the first and second half of Phase 2. However, the RTs for atypical readers, show minimal change, if any, across Phase 2 and no statistically significant group differences were observed for behavioral data.

In terms of waveforms, typical readers showed a reversal from higher HP amplitudes in Phase 1 and Phase 2a to higher LP amplitudes in Phase 2b. This could be because, saliency for the LP target grew over time as the change in its probability of occurrence was encoded. The only reliable finding was a group difference at the central-posterior region for HP amplitudes in Phase 1 only; but this informative of an amplitude difference not a learning difference across groups.

Another interesting pattern is in the topological-plot views of matched groups within Phase 2. Whereas the typical group topological-views reflect a shift from front-central to posterior in terms of higher HP amplitudes between first and second half, the atypical adults reveal exactly the opposite pattern. This could be indicative of a learning difference across groups in terms of encoding auditory information. This could have implications for the phonological theory of dyslexia because phonological processing if understood in terms of sound-to-mapping, must rely on both auditory as well as visual cognitive processes. It could be that the atypical readers did not learn the HP-LP difference in Phase 1 and consequently the switch in predictability conditions in Phase 2 to the same degree as the typical readers because of poor sensitivity to sound statistics (Banai & Ahissar, 2018). According to their theory, Banai and Ahissar (2018) postulate that atypical readers encounter impaired categorical perception of continuous speech because (1) their implicit memory of previous stimuli decays at a faster rate than typical readers; and (2) that their stimulus-adaptation processes are shorter (in the present case, learning the predictability switch in Phase 2).

Thus, unlike the visual-motor task, the current results revealed no group differences regarding predictability across phase. However, the atypical-reader results differed from their typical counterparts based on visual appearance of the RTs, which barely differed within Phase 2; and topological-plot views that indicated a posterior-anterior (HP-LP amplitude difference) shift in Phase 2 in contrast to typical readers. If findings from statistical analyses had been in line with the (visual) discrepancies across groups then the results of this task could be construed as a general auditory statistical learning deficit, one which indirectly influences phonological processing. However, in the absence of significant group differences, no deficit was explicitly observed for this task.

4.6 Correlations

Only scores on symbol search for atypical readers in the AGL task were found to be positively correlated with ERP amplitude differences of grammaticality. This correlation that was found in right posterior regions, during the 500-700ms time window only might suggest a that cognitive processes recruited during the symbol search task were similar to those mechanism activated for grammatical vs. non-grammatical items in the AGL task.

The absence of additional correlations could be due to the fact that the knowledge types indexed with current non-linguistic stimuli were not sensitive enough to be correlated with the other normed measures such as pseudoword decoding and digit span to name a few.

4.7 Limitations

An obvious weakness of the current study was the inability to match on age and/or reading ability as is typically done in the literature (Howard et al., 2006; Nigro et al., 2016). This limit was somewhat tempered by the fact that (1) participants were matched on their memory ability, and (2) only one correlation was found between age or reading scores and other behavioral/ ERP measures. Additionally, the low sample size for atypical readers did not help when comparing across groups for deficits in implicit-statistical learning.

The artificial grammar learning task was only administered as a visual assessment and did not have an auditory counterpart. In a future study, it would be beneficial to have an auditory version of the task (similar to Silva et al., 2017) to be able to compare across sensory domains, especially because phonological skills function cross-modally.

The number of trials in Phase 1 (for the predictability tasks) was less than the number of trials included in Phase 2a and 2b. Fewer trials in Phase 1 resulted in unequal exposure of the predictability conditions. However, increasing this exposure period to equate trial numbers across phases may also affect later learning in Phase 2a and 2b. To clarify, it is difficult to acquire balance between administering an optimal number of trials so that on the one hand, ensuring participants are able to learn the varying predictability of Phase 1, but at the same time also administering just enough trials so that participants quickly learn the switch to equal predictability in Phase 2, without perseverating on Phase 1 (probabilistic) predictability conditions. Such is the dilemma in engineering learning tasks that require participants to learn and relearn new associations in a short period of time. Thus, the current design did capture learning (or lack thereof) but performance might be enhanced by an increased number of trials in Phase 1.

Additionally, according to the majority of participants' self-reports, the auditory-motor SL task was rated as the most difficult compared to the rest. This indicates that tasks may not have been perceived as equal in terms of difficulty level and a future study would address this issue accordingly. Although current stimuli design was based on established findings by Saffran et al., (1999), it could be that rate of decay of memory/attention for the tones used might vary across individuals and might not be the same as that of the visual task (both current tasks were equated for stimulus duration and ISI). One way to do this would be to present auditory stimuli that vary in stimulus intensity and duration, frequency or even inter-stimulus-onset to find optimal thresholds for auditory statistical learning in adults.

One limitation that comes to mind post-hoc, would be to redo current analyses but with a learner vs. non-learner distinction instead of a typical vs atypical reader comparison. Because, for example, in the AGL task, learning seemed to hover around chance levels poor learning capacity. But it may be that some learned better than others. Separating learners from non-learners will first reveal at a basic level whether implicit-statistical learning across participants differed by paradigm as well as whether this learning was corroborated by both behavioral and neurophysiological data. A next step would then be to investigate whether a participant's reading ability differed within the learner and non-learner group.

The general lack of learning differences might be due to the fact that (a) learning, at least in the AGL paradigm, was not above chance for the typical group to begin with; and (b) the stimuli were non-linguistic as opposed to linguistic. It could be that learning involving such non-linguistic stimuli was difficult for both groups and that a few hours of exposure were not enough to reflect a level of learning in line with a task using linguistic stimuli.

Furthermore, in a future study, multiple sessions instead of a single experimental session would help illuminate the effects of consolidation on statistical learning. Such a study would be similar to Silva et al. (2017) who showed enhanced performance (for participants without reading difficulty) on artificial grammar learning tasks over time as do others even on tasks with embedded statistical regularities (Bennet et al., 2008; Du & Kelly, 2013). It is important to investigate whether consolidation affects the sequential-learning ability of adults with dyslexia, as this could have far-reaching implications for reading interventions and reading acquisition in general. For instance, if research supports the role of consolidation in learning, it may be beneficial for all individuals—but more so for atypical readers—to allow for consolidation with regards to implicit-statistical learning (e.g., of syntax, spelling, reading, playing a musical instrument). Additionally, multiple sessions would also allow time for administration of more comprehensive normed assessments, such as those measuring musical aptitude, language, executive function, memory, attention, phonological and orthographical skills. This would generate a more holistic understanding of how such incidental learning is correlated with other cognitive processes.

Also noteworthy is that the atypical readers were, on average, college-educated, older individuals who had prior experience with experimental testing, and a majority were referred for study participation after clinical intervention. All of this may have influenced learning and the awareness of underlying patterns in the task used.

4.8 Conclusions

In sum, no learning deficit was found when comparing typical and atypical readers. However, both task paradigms seem to have elicited other differences via behavioral responses and ERP waveforms, indicating potential differences in the influence of grammaticality and CS knowledge. In addition, (visual, but not statistical) differences in behavioral and ERP data were observed across groups. Among these observations were slower RTs overall and differences in the topology of waveform differences. However, results were comparable across groups.

To ground all, or any, of these results in any one particular theory of dyslexia is difficult as there could be multiple reasons for the group differences observed in the present study. Overall, slower response times could be attributed to deficits in temporal processing (Conlon et al., 2011) and different trends in endorsement rates to differences in visual attention (Bosse, Tainturier & Valdois, 2007) as well as procedural-cerebellar functioning (Gabay et al., 2015; Nicolson et al., 2001). A future study design would benefit from noting the limitations previously outlined in the present study along with the current findings. These could prove valuable for building on prominent and lesser-known theories as well as aid in further evaluating types of information acquired during implicit-statistical learning tasks across with both typical and atypical readers.

This study was the first to investigate behavioral and neural mechanisms underlying implicit-statistical learning with non-linguistic stimuli by using paradigms eliciting different types of knowledge, such as algebraic patterns, ordinal knowledge, chunking and transition-timing, in both typical and atypical readers. The statistical learning paradigm used to elicit transition-timing knowledge was administered in the visual-motor and auditory-motor domain and the other knowledge types pertain to the artificial grammar paradigm. It is important for future studies further to investigate whether the current study findings are replicable across different samples of learners and non-learners with reading difficulty.

Thus, overall, the current study highlights that learning is not the same across SL paradigms for typical and atypical readers and additionally, also tends to vary based on whether it is indexed behaviorally or neurophysiologically. Before making strong conclusions about learning, however, it is important for future studies focused on the nature of implicit-statistical learning to also test typical and atypical readers on underlying knowledge elicited by task type, but with both linguistic and non-linguistic stimuli on more than one session

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APPENDICES

Appendix A: Additional Descriptives by experimental group for each participant

number	group	age (Y/M)	sex	handedness	ethnicity	diagnoses
9901	atypical	27.43	M	R	White	learning disorder
9902	atypical	24.43	F	R	Black/ African American	
9903	atypical	29.30	M	A	White	learning disorder
9904	atypical	30.75	F	A	White	learning disorder
9905	atypical	20.09	F	R	White	
9906	atypical	24.26	M	L	White	ADHD, dyslexia
9907	atypical	38.06	F	R	Black/ African American	learning disorder
9908	atypical	26.38	F	R	White	learning disorder
9909	atypical	24.08	M	R	White	Learning disorder, Language disorder, Speech Impairment and OCD, medication (Prozac 30 mg a day)
9910	atypical	23.24	M	A	White	learning disorder
9911	atypical	60.47	F	R	Other	ADHD
9912	atypical	65.64	F	R	White	ADHD
9913	atypical	48.37	F	R	Black/ African American	learning disorder and auditory processing disorder
9914	atypical	21.40	F	A	White	
9915	atypical	19.87	M	R	White	
9916	atypical	24.96	F	R	White	
9701	typical	18.61	F	R	Asian	
9702	typical	29.72	F	R	Black/ African American	
9703					Hispanic/ Latino	
9704	typical	23.89	F	R	Black/ African American	
9705	typical	18.85	F	R	American Indian/ Alaska Native	
9706	typical	18.21	M	A	Asian	
9707	typical	19.54	M	R	Asian	
9708	typical	18.45	F	R	White	
9709	typical	18.05	F	R	White	

9710	typical	18.79	M	R	Black/ African American
9711	typical	18.33	F	R	Mixed race
9712	typical	18.94	M	R	Hispanic / Latino
9713	typical	18.69	F	R	Asian
9714	typical	18.59	F	R	White
9715	typical	19.33	F	A	Black/ African American
9716	typical	22.67	F	R	Asian
9717	typical	21.33	F	R	White
9718	typical	22.46	F	R	White
9719	typical	18.79	F	R	Black/ African American
9720	typical	19.88	P	A	Mixed race
9721	typical	18.73	F	R	Asian
9722	typical	19.68	M	R	Black/ African American
9723	typical	20.36	F	R	Asian
9724	typical	20.12	M	A	White
9725	typical	19.44	F	R	Hispanic/ Latino
9726	typical	19.20	M	R	Black/ African American
9727	typical	28.56	F	R	Hispanic/ Latino
9728	typical	18.20	F	R	Hispanic/ Latino
9729	typical	18.32	F	R	Black/ African American
9730	typical	18.05	F	R	Hispanic/ Latino
9731	typical	22.62	M	R	Other
9732	typical	18.46	F	R	White
9733	typical	18.54	P	R	Asian
9734	typical	19.10	F	R	Black/ African American
9735	typical	18.47	F	R	Hispanic/ Latino
9736	typical	19.02	F	R	Hispanic / Latino
9737	typical	19.68	P	R	White

[Sex: F = female; M = Male; P = Prefer not to disclose; Handedness: L = left; R = right; A = ambidextrous]

Appendix B: Questionnaires Used

Appendix B.1: Participant Information Questionnaire

*(*Required)*

1. Participant Number *__________ (filled by experimenter)

2. Date of Birth * __________ (Example: December 15, 2012)

3. Today's Date * __________ (Example: December 15, 2012)

4. I certify that I am 18 years old as of today. *
   - o Yes
   - o No

5. Gender *
   - o Male
   - o Female
   - o Prefer not to disclose

6. I describe myself as *
   - o American Indian or Alaska Native
   - o Asian
   - o Black or African American
   - o Hispanic or Latino
   - o Native Hawaiian or Other Pacific Islander
   - o White
   - o Mixed race
   - o Other

7. What is your native language? *

8. Are you a fluent speaker of a language other than your native language? *
   - o Yes
   - o No (Skip to question 10)

Language

9. Please list all languages you speak along with fluency level (basic, intermediate, fluent) for each language *

Cognitive

10. Are you deaf or hard of hearing? *
    - o Yes

- No

11. Do you use a hearing aid or hearing aids? *
   - Yes
   - No

12. Do you have a visual impairment? *
   - Yes
   - No

13. Do you use visual aids? (corrective lenses, reading glasses, etc.) *
   - Yes
   - No

14. Please check if you been diagnosed with any of the following:
   - Autism
   - Learning disorder
   - Language disorder
   - Attention disorder (ADHD)
   - Blindness
   - Developmental Disability
   - Speech Impairment
   - Vision Impairment (not corrected by glasses/ lenses)
   - Other diagnosed disorder

15. If you indicated 'other' diagnosed disorder in your previous response, please list the disorder(s) below
   ----

16. Are you currently under the influence of any prescription drug, illegal drug or alcohol that might affect your performance in this experiment? *
   - Yes
   - No

17. How much caffeine (coffee, tea, energy drinks, etc) have you consumed in the last 5 hours? *
   - None
   - 1 - 2 cups coffee/ tea
   - 2 - 3 cups coffee/ tea
   - more than 3 cups coffee/ tea
   - 1 or more energy drinks
   - 1 or more caffeinated soft drinks/ sodas

18. Reading
   - Do you like to read in your free time? *
   - Yes

- No *(Stop filling out this form)*.

19. Reading contd.
  - How often do you read? *
  - once or twice a year
  - once or twice a month
  - once or twice a week
  - daily

20. How fast do you typically read? *
  - 2-3 mins a page
  - 5-6 mins a page

Appendix B.2: Adult ADHD Self-Report Scale (ASRS-v1.1) Symptom Checklist

[*Participants responded to the questions below by rating themselves using the options: Never, Rarely, Sometimes, often, very often*]

1. How often do you have trouble wrapping up the final details of a project, once the challenging parts have been done?
2. How often do you have difficulty getting things in order when you have to do a task that requires organization?
3. How often do you have problems remembering appointments or obligations?
4. When you have a task that requires a lot of thought, how often do you avoid or delay getting started?
5. How often do you fidget or squirm with your hands or feet when you have to sit down for a long time?
6. How often do you feel overly active and compelled to do things, like you were driven by a motor?
7. How often do you make careless mistakes when you have to work on a boring or difficult project?
8. How often do you have difficulty keeping your attention when you are doing boring or repetitive work?
9. How often do you have difficulty concentrating on what people say to you, even when they are speaking to you directly?
10. How often do you misplace or have difficulty finding things at home or at work?
11. How often are you distracted by activity or noise around you?
12. How often do you leave your seat in meetings or other situations in which you are expected to remain seated?
13. How often do you feel restless or fidgety?
14. How often do you have difficulty unwinding and relaxing when you have time to yourself?
15. How often do you find yourself talking too much when you are in social situations?
16. When you're in a conversation, how often do you find yourself finishing the sentences of the people you are talking to, before they can finish them themselves?
17. How often do you have difficulty waiting your turn in situations when turn taking is required?
18. How often do you interrupt others when they are busy?

Appendix: B.3: Handedness Questionnaire

Instructions: For each of the activities below, please indicate:
Which hand so you prefer for that activity?
Do you ever use the other hand for the activity?
Which hand do you prefer to use when:

Which hand do you prefer to use when:				**Do you ever use the other hand?**
		No pref		__Yes
Writing	Left__	__	__Right	__Yes
Drawing	Left__	__	__Right	__Yes
Throwing	Left__	__	__Right	__Yes
Using Scissors	Left__	__	__Right	__Yes
Using a toothbrush	Left__	__	__Right	__Yes
Using a knife(witout a fork)	Left__	__	__Right	__Yes
Using a spoon	Left__	__	__Right	__Yes
Striking a match	Left__	__	__Right	__Yes
Opening a box (holding the lid)	Left__	__	__Right	__Yes
Items below are not on the standard Inventory:				
Holding a computer mouse	Left__	__	__Right	__Yes
Using a key to unlock a door	Left__	__	__Right	__Yes
Holding a hammer	Left__	__	__Right	__Yes
Holding a brush or comb	Left__	__	__Right	__Yes
Holding a cup while drinking	Left__	__	__Right	__Yes

This handedness questionnaire was adapted from: Oldfield, R.C. "The assessment and analysis of handedness: the Edinburgh inventory." Neuropsychologia. 9(1):97-113. 1971.

Appendix B.4: *The Ollen Musical Sophistication Index (OMSI)*

Instructions: The OMSI is a tool to aid researchers in classifying their research participants as more or less musically sophisticated. To obtain your score, please indicate an answer for every question unless you are specifically directed to skip one:

1. How old are you today?

_____ age in years

2. At what age did you begin sustained musical activity? "Sustained musical activity" might include regular music lessons or daily musical practice that lasted for at least three consecutive years. If you have never been musically active for a sustained time period, please answer with zero.

______ age at start of sustained musical activity

3. How many years of private music lessons have you received? If you have received lessons on more than one instrument, including voice, give the number of years for the one instrument/ voice you've studied longest. If you have never received private lessons, answer with zero.

______ years of private lessons

4. For how many years have you engaged in regular, daily practice of a musical instrument or singing? 'Daily' can mean defined as 5 to 7 days per week. A 'year' can be defined as 10 to 12 months. If you have never practiced regularly for fewer than 10 months, answer with zero.

______ years of regular practice

5. Which category comes nearest to the amount of time you currently spend practicing an instrument (or voice)? Count individual practice time only; no group rehearsals.

o I rarely or never practice singing or playing an instrument
o About 1 hour per month
o About 1 hour per week
o About 15 minutes per day

- About 1 hour per day
- More than 2 hours per day

6. Have you ever enrolled in any music courses offered at college (or university)?

- Yes
- No (*go to question 8*)

7. (If yes) How much college level coursework in music have you completed? If more than one category applies, select your most recently completed level.

- 1 or 2 non major (e.g. music appreciation, playing or singing in an ensemble)
- 3 or more courses for NON-members
- An introductory or preparatory music program for Bachelor's level work
- 1 year of full time coursework in a Bachelor of Music degree program (or equivalent)
- 2 years of full time coursework in a Bachelor of Music degree program (or equivalent)
- 3 or more years of full time coursework in a Bachelor of Music degree program (or equivalent)
- Completion of a Bachelor of Music degree program (or equivalent)
- One or more graduate-level music courses or degrees

8. Which option best describes your experience at composing music?

- Have never composed any music
- Have composed bits and pieces, but have never completed a piece of music
- Have composed one or more completed pieces, but none have been performed
- Have composed pieces as assignments or projects for one or more music classes; one or more of my pieces have been performed and/ or recorded within the context of my educational environment.
- Have composed pieces that have been performed for a regional or national audience (e.g., nationally known performer or ensemble, major concert venue, broadly distributed recording)

9. To the best of your memory, how many live concerts (or any style, with free or paid permission) have you attended as an audience member in the past 12 months? Please do not include regular religious services in your count, but you may include special musical productions or events.

- None
- 1 - 4
- 5 – 8
- 9 – 12

- 13 or more

10. Which title best describes you?

- Nonmusician
- Music-loving nonmusician
- Amateur musician
- Serious amateur musician
- Semiprofessional musician
- Professional musician

Appendix B.5: Participant Awareness Questionnaire

Circles *(* Required)*

18. **Think about the circles task you did. Describe what you remember about the task. ***

Symbols

2. **Think about the symbols computer task you did. Describe what you remember about the task. ***

Sounds

3. **Think about the sounds computer task you did. Describe what you remember about the task. ***

General Observations

4. **Did you ever notice a pattern in any tasks? ***

- o Yes They all had patterns
- o Some of them had patterns but not all of them
- o There seemed to be no pattern at all *(skip to question 9)*

Patterns

18. **Indicate possible pattern occurrence by task ***

	Very often	Only sometimes	Never
Circles			
Symbols			
Sounds			

18. **At what point did you notice the pattern? ***

	Start	Middle	End	Not for this task
Circles				
Symbols				
Sounds				

18. **Did any one task help you to find a pattern in another? ***

- No they all seemed very different *(skip to question 9)*
- I didn't really think about that *(skip to question 9)*
- Yes definitely

8. **Explain how one or more tasks may have influenced your performance on another. Please be specific (list the task by name – Circles, Symbols, sounds). ***

Strategies

9. **Did you use a strategy to help you remember items in any task? ***

- Yes
- No *(skip to question 11)*

Strategy Explanation

18. **Explain the strategy you used ***

Labels

18. **In any task did you use mental labels to remember items as they were presented? (e.g. house, chair, triangle, etc.) ***

- Yes
- No *(skip to question 14)*

Indicate Labels

18. **List all labels you used by task. Please be specific (Circles, symbols, sounds) ***

Label use frequency

13. **How often did you use labels? ***

	Rarely	Sometimes	Very Often
Circles			
Symbols			
Sounds			

General

14. **Rate task difficulty level ***

	Easy	Difficult
Circles		
Symbols		

Sounds		

15. **Did it ever seem like there were mistakes in any of the tasks? ***

	Yes	No
Circles		
Symbols		
Sounds		

16. **Did you feel tired during any of the tasks?**

- o Yes
- o No

17. **At what point did you feel tired? ***

	Start	Middle	End
Circles			
Symbols			
Sounds			

18. **Indicate how long the tasks seemed to you ***

	Short	Not very long	Long
Circles			
Symbols			
Sounds			

Appendix C: Supplemental Results

Appendix C.1: Supplemental Results for the Artificial Grammar Learning Task

Table 4 Typical: Sureness responses (%) in each grammatical category

Sureness rating	GH	GL	NGH	NGL
I was guessing	04	09	04	09
I was mostly guessing	13	14	13	09
I am mostly sure	39	26	35	22
I am sure	44	48	48	61

Table 5 Atypical: sureness responses per group (%) by grammatical category

Sureness rating	GH	GL	NGH	NGL
I was guessing	00	00	00	00
I was mostly guessing	25	33	25	25
I am mostly sure	17	08	25	17
I am sure	58	58	50	58

Table 6 Correlations: Behavioral scores on AGL for Typical group

	PA	Age	Reading	PWD	Spelling	DS	SS	OMSI	ADHD	Gram[1]	CS[2]
PA											
Age	0.022										
Reading	-0.242	-0.057									
PWD	-0.051	-0.365	.472*								
Spelling	-0.235	-0.052	.475*	.437*							
DS	-0.213	0.204	-0.114	-0.103	0.353						
SS	0.066	-0.348	0.318	0.222	0.335	-0.045					
OMSI	0.248	-0.071	-0.085	-0.025	-0.174	-.454*	-0.201				
ADHD	0.323	0.391	-0.015	-0.340	-0.233	-0.197	-0.131	-0.056			
Gram[1]	0.117	-0.033	-0.228	0.104	0.105	-0.040	-0.054	0.308	-0.310		
CS[2]	-0.285	0.050	-0.070	-0.402	-0.095	.489*	-0.336	-0.260	-0.012	-0.161	

*Correlation is significant at the 0.05 level (2-tailed); N = 22; [1]G-NG; [2]HCS-LCS

Table 7 Correlations: ERP scores on AGL (500-700ms time window) for the typical group

	PA	Age	Reading	PWD	Spelling	DS	SS	OMSI	ADHD	Lan[1]	Lpo[1]	Lan[2]	Lpo[2]	Ran[1]	Rpo[1]	Ran[2]
PA																
Age	-0.125															
Reading	-0.165	0.098														
PWD	-0.057	-0.267	.561**													
Spelling	-0.296	0.008	0.388	.420*												
DS	-0.200	0.128	0.108	0.065	0.391											
SS	0.216	-0.178	-0.067	0.005	0.009	0.063										
OMSI	0.023	0.280	0.053	0.009	-0.023	-0.283	-0.217									
ADHD	0.256	0.003	-0.289	-.427*	-.434*	-0.112	-0.206	-0.204								
Lan[1]	0.011	0.023	0.095	0.215	-0.036	0.048	-0.147	0.358	-0.117							
Lpo[1]	-0.283	-0.138	-0.014	-0.124	0.069	0.001	-0.300	0.136	0.264	-0.155						
Lan[2]	-0.034	-0.123	0.337	0.185	0.167	0.264	0.127	0.169	-0.351	0.110	.412*					
Lpo[2]	-0.136	-0.177	-0.154	-0.250	-0.233	-0.291	0.105	-0.161	0.264	-0.380	0.008	-0.297				
Ran[1]	0.328	0.096	-0.103	-0.087	-0.100	-0.022	0.130	-0.098	-0.255	0.055	-.843**	-.421*	-0.127			
Rpo[1]	-0.091	-0.165	-0.293	-0.199	-0.278	-0.099	-0.051	-0.004	0.381	-.451*	.408*	-0.194	0.292	-0.366		
Ran[2]	0.011	0.054	0.201	0.334	0.282	0.239	-0.085	0.262	-0.356	0.112	0.226	.477*	-.802**	-0.178	0.025	
Rpo[2]	-0.102	0.223	-0.092	-0.051	0.023	-0.188	-0.180	-0.072	0.176	0.016	-0.264	-.677**	.516**	0.207	-0.039	-.695**

*Correlation is significant at the 0.05 level (2-tailed); **Correlation is significant at the 0.01 level (2-tailed); N = 25; [1] NG-G; [2] LCS-HCS

Table 8 Correlations: ERP scores on AGL (700-900ms time window) for the typical group

	PA	Age	Reading	PWD	Spelling	DS	SS	OMSI	ADHD	Lan[1]	Lpo[1]	Lan[2]	Lpo[2]	Ran[1]	Rpo[1]	Ran[2]
PA																
Age	-0.125															
Reading	-0.165	0.098														
PWD	-0.057	-0.267	.561**													
Spelling	-0.296	0.008	0.388	.420*												
DS	-0.200	0.128	0.108	0.065	0.391											
SS	0.216	-0.178	-0.067	0.005	0.009	0.063										
OMSI	0.023	0.280	0.053	0.009	-0.023	-0.283	-0.217									
ADHD	0.256	0.003	-0.289	-.427*	-.434*	-0.112	-0.206	-0.204								
Lan[1]	0.045	0.066	0.142	0.185	-0.004	0.087	-0.146	0.372	-0.138							
Lpo[1]	-0.091	-0.024	.416*	0.225	0.218	0.261	0.049	0.157	-0.376	0.139						
Lan[2]	-0.317	-0.191	-0.014	-0.050	0.207	0.123	-0.289	0.024	0.176	-0.227	.434*					
Lpo[2]	-0.068	-0.229	-0.192	-0.188	-0.222	-0.314	0.086	-0.131	0.316	-0.358	-0.392	-0.078				
Ran[1]	0.306	0.126	0.034	-0.047	-0.124	-0.045	0.106	-0.039	-0.214	0.125	-.402*	-.838**	-0.038			
Rpo[1]	-0.011	0.083	0.155	0.287	0.253	0.239	-0.094	0.249	-0.367	0.110	.511**	0.278	-.796**	-0.261		
Ran[2]	-0.068	-0.264	-0.353	-0.190	-0.290	-0.107	0.016	-0.103	0.373	-.461*	-0.251	0.319	0.238	-0.395	0.058	
Rpo[2]	-0.045	0.142	-0.106	-0.003	-0.003	-0.151	-0.155	-0.077	0.215	0.097	-.665**	-0.291	.512**	0.254	-.665**	-0.018

*Correlation is significant at the 0.05 level (2-tailed); **Correlation is significant at the 0.01 level (2-tailed); N = 25; [1] NG-G; [2] LCS-HCS

Table 9 Correlations: Behavioral scores on AGL for the atypical group

	PA	Age	Reading	PWD	Spelling	DS	SS	OMSI	ADHD	Gram[1]	CS[2]
PA											
Age	0.051										
Reading	0.205	0.336									
PWD	0.077	-0.095	0.469								
Spelling	0.000	0.517	0.529	0.130							
DS	0.000	0.347	0.552	0.542	0.354						
SS	-0.206	0.063	.587*	.733**	0.312	0.408					
OMSI	0.051	-0.407	-.738**	0.028	-0.358	-0.382	-0.280				
ADHD	0.233	0.360	0.458	0.096	0.131	0.261	0.060	-0.250			
Gram[1]	0.129	-0.172	0.150	0.389	-0.503	0.016	0.198	0.203	0.412		
CS[2]	-.690*	-0.297	-0.189	-0.263	-0.232	-0.382	0.000	0.062	-0.150	0.047	

*Correlation is significant at the 0.05 level (2-tailed); *N* = 12; [1]G- NG; [2]HCS-LCS

Table 10 Correlations: ERP scores on AGL (500-70ms time window) for the atypical group

	PA	Age	Reading	PWD	Spelling	DS	SS	OMSI	ADHD	Lan[1]	Lpo[1]	Lan[2]	Lpo[2]	Ran[1]	Rpo[1]	Ran[2]	Rpo[2]
PA																	
Age	-0.418																
Reading	-0.028	0.254															
PWD	-0.252	-0.144	0.576														
Spelling	0.084	0.210	0.493	0.158													
DS	-0.559	0.291	0.565	0.324	0.084												
SS	-0.365	-0.007	0.426	.689*	0.416	0.170											
OMSI	0.503	-0.368	-0.543	-0.448	-0.214	-0.404	-0.194										
ADHD	-0.281	0.363	0.440	0.568	0.106	0.473	0.455	-0.154									
Lan[1]	-0.139	0.049	-0.042	0.060	0.126	0.144	-0.176	-0.105	-0.250								
Lpo[1]	0.307	-0.343	0.127	0.340	-0.357	-0.246	0.021	0.021	0.116	-0.133							
Lan[2]	0.084	-0.371	0.289	0.460	0.189	0.151	0.106	-0.084	0.000	0.210	0.315						
Lpo[2]	-0.084	-0.469	-0.556	-0.158	0.014	-0.144	0.056	0.487	-0.222	0.406	-0.105	0.070					
Ran[1]	-.585*	0.350	-0.148	-0.074	-0.231	0.221	0.042	-0.245	0.286	-0.434	0.070	-0.133	-0.140				
Rpo[1]	0.028	-0.063	0.387	0.442	0.385	0.189	.711**	0.151	.663*	-0.462	0.056	-0.091	0.014	0.091			
Ran[2]	-0.139	0.007	0.324	-0.147	-0.007	0.347	0.120	-0.193	-0.106	-0.392	0.077	-0.273	-0.224	0.364	0.245		
Rpo[2]	-0.195	0.217	-0.134	-0.284	-0.189	-0.130	0.085	-0.130	-0.148	-0.182	-0.007	-.839**	-0.056	0.238	0.077	.580*	

*Correlation is significant at the 0.05 level (2-tailed); **Correlation is significant at the 0.01 level (2-tailed); $N = 12$; [1]Ngram-gram; [2]LCS-HCS

Table 11 Correlations: ERP scores on AGL (700-90ms time window) for the atypical group

	PA	Age	Reading	PWD	Spelling	DS	SS	OMSI	ADHD	Lan[1]	Lpo[1]	Lan[2]	Lpo[2]	Ran[1]	Rpo[1]	Ran[2]	Rpo[2]
PA																	
Age	-0.418																
Reading	-0.028	0.254															
PWD	-0.252	-0.144	0.576														
Spelling	0.084	0.210	0.493	0.158													
DS	-0.559	0.291	0.565	0.324	0.084												
SS	-0.365	-0.007	0.426	.689*	0.416	0.170											
OMSI	0.503	-0.368	-0.543	-0.448	-0.214	-0.404	-0.194										
ADHD	-0.281	0.363	0.440	0.568	0.106	0.473	0.455	-0.154									
Lan[1]	0.139	-0.140	-0.077	-0.137	0.161	-0.098	-0.331	-0.084	-.653*								
Lpo[1]	0.418	-0.322	0.120	0.186	-0.343	-0.242	-0.176	0.074	-0.042	0.056							
Lan[2]	-.697*	0.273	-0.141	0.175	-0.182	0.158	0.239	-0.392	0.307	-0.420	0.000						
Lpo[2]	-0.084	-0.007	0.310	0.368	0.259	0.239	.648*	0.144	.684*	-.741**	-0.112	0.294					
Ran[1]	0.028	-0.343	0.275	0.414	0.196	0.196	0.113	-0.060	-0.021	0.252	0.322	-0.056	-0.091				
Rpo[1]	-0.139	-0.441	-0.521	-0.081	0.028	-0.116	0.113	0.438	-0.180	0.252	-0.161	-0.042	-0.070	0.161			
Ran[2]	-0.251	0.056	0.261	-0.189	0.014	0.442	0.056	-0.196	-0.138	-0.070	0.028	0.280	0.252	-0.175	-0.189		
Rpo[2]	-0.195	0.217	-0.134	-0.284	-0.189	-0.130	0.085	-0.130	-0.148	-0.133	-0.070	0.238	0.063	-.825**	-0.098	0.517	

*Correlation is significant at the 0.05 level (2-tailed); **Correlation is significant at the 0.01 level (2-tailed); N = 12; [1]Ngram-gram; [2]LCS-HCS

Appendix C.2: Supplemental Results for the Probabilistic Learning Task (Visual)

Table 12 Correlations: Behavioral scores on VSL for Typical group

	PA	Age	Reading	PWD	Spelling	DS	SS	OMSI	ADHD	Phase 1[1]	Phase 2a[1]	Phase 2b[1]
PA												
Age	-0.099											
Reading	-0.145	0.087										
PWD	0.042	-0.141	.679**									
Spelling	-0.177	0.191	.532**	.471**								
DS	-0.183	0.143	0.223	0.079	.388*							
SS	0.164	-0.136	0.031	0.018	0.083	0.048						
OMSI	0.119	0.085	0.152	0.008	-0.070	-0.223	-0.138					
ADHD	0.329	0.014	-0.175	-0.228	-0.146	-0.078	-0.048	-0.029				
Phase 1[1]	0.195	-0.181	0.138	0.127	0.031	-0.183	-0.068	0.199	0.045			
Phase 2a[1]	-0.022	-.410*	0.141	0.166	-0.105	-0.200	0.119	0.154	-0.185	.597**		
Phase 2b[1]	0.051	-0.301	0.015	0.086	-.363*	-0.253	-0.005	0.090	0.141	.425*	.533**	

*Correlation is significant at the 0.05 level (2-tailed); **Correlation is significant at the 0.01 level (2-tailed); N = 34; [1] LP - HP

Table 13 Correlations: ERP scores on VSL (400-700ms time window) for the atypical group

	PA	Age	Reading	PWD	Spelling	DS	SS	OMSI	ADHD	Phase-1[1]	Phase-2a[1]
PA											
Age	-0.059										
Reading	-0.112	0.009									
PWD	0.063	-0.175	.547**								
Spelling	-0.254	0.121	.472**	.492**							
DS	-0.221	0.138	0.199	0.107	0.319						
SS	0.115	-0.083	0.054	0.072	0.055	0.044					
OMSI	0.043	0.011	0.102	0.043	-0.063	-0.309	-0.176				
ADHD	.341*	0.023	-0.115	-0.242	-0.186	-0.099	-0.063	-0.089			
Phase-1[1]	-.368*	-0.064	-0.040	-0.132	-0.111	0.105	-0.175	-0.027	0.024		
Phase-2a[1]	-0.191	0.033	0.250	0.083	-0.089	-0.121	.369*	-0.026	-0.325	0.196	
Phase2-b[1]	0.007	-0.143	0.148	-0.015	0.090	-0.265	-0.147	0.339	-0.180	0.182	-0.205

*Correlation is significant at the 0.05 level (2-tailed); **Correlation is significant at the 0.001 level (2-tailed); N = 34; [1] HP-LP for POz

Table 14 Correlations: Behavioral scores on VSL for the atypical group

	PA	Age	Reading	PWD	Spelling	DS	SS	OMSI	ADHD	Phase 1[1]	Phase 2a[1]
PA											
Age	-0.051										
Reading	0	0.556									
PWD	-0.283	-0.049	0.265								
Spelling	0.307	.706*	0.528	-0.042							
DS	-0.514	.779**	0.445	0.176	0.225						
SS	-0.284	0.092	0.43	0.48	0.328	0.163					
OMSI	0.205	.683*	0.564	0.116	0.382	.620*	-0.067				
ADHD	0.18	-0.004	-0.371	0.025	0.281	-0.345	-0.265	-0.163			
Phase 1[1]	.590*	-0.441	-0.272	0.158	-0.266	-0.446	-0.36	0.13	0.1		
Phase 2a[1]	-0.257	-0.225	-0.201	0.203	-0.372	-0.085	0.271	-0.439	-0.299	-0.214	
Phase 2b[1]	-0.41	-0.196	-0.437	-0.316	-0.217	-0.028	0.286	-.637*	-0.249	-0.406	0.554

*Correlation is significant at the 0.05 level (2-tailed); **Correlation is significant at the 0.01 level (2-tailed); *N* = 12; [1]LP - HP

Table 15 Correlations: ERP scores on VSL (400-700ms time window) for the atypical group

	PA	**Age**	**Reading**	**PWD**	**Spelling**	**DS**	**SS**	**OMSI**	**ADHD**	**Phase-1[1]**	**Phase-2a[1]**
PA											
Age	0.035										
Reading	0.212	0.292									
PWD	-0.070	-0.147	.531*								
Spelling	0.105	0.425	0.426	0.066							
DS	-0.088	0.297	0.431	0.412	0.048						
SS	-0.192	-0.093	0.466	.656**	0.356	0.163					
OMSI	0.000	-0.211	-.622*	-0.244	-0.075	-0.241	0.033				
ADHD	0.105	0.266	0.315	0.339	0.090	0.202	0.250	0.032			
Phase-1[1]	0.035	-0.125	-0.042	-0.295	-0.393	0.027	-0.329	-0.363	-0.007		
Phase-2a[1]	-.523*	-0.307	-0.148	-0.050	-0.450	0.199	-0.002	-0.202	-0.317	0.418	
Phase2-b[1]	0.244	-0.211	0.348	-0.238	-0.007	-0.219	-0.200	-0.386	-0.241	0.121	0.168

Appendix C.3: Supplemental Results for the Probabilistic Learning Task (Auditory)

Table 16 Correlations: Behavioral scores on ASL for Typical group

	PA	Age	Reading	PWD	Spelling	DS	SS	OMSI	ADHD	Phase 2a[1]	Phase 2b[1]
PA											
Age	-0.122										
Reading	-0.233	0.144									
PWD	0.061	-0.088	.631**								
Spelling	-0.392	0.246	.599**	0.400							
DS	-0.216	0.346	-0.052	-0.243	-0.043						
SS	0.043	0.106	-0.100	-0.030	0.139	0.102					
OMSI	0.067	-0.070	.426*	0.254	0.255	-0.035	-0.217				
ADHD	0.154	-0.036	-0.012	-0.095	-0.026	0.176	0.040	-0.210			
Phase 2a[1]	-0.110	-0.069	-0.114	-0.114	0.155	0.240	0.096	-0.169	0.177		
Phase 2b[1]	0.073	-0.141	0.059	-0.195	0.144	0.072	0.163	0.118	0.094	.493*	

*Correlation is significant at the 0.05 level (2-tailed); **Correlation is significant at the 0.01 level (2-tailed); N = 24; [1] LP - HP

Table 17 Correlations: ERP scores on AGL (500-700ms time window) for the typical group

	PA	Age	Reading	PWD	Spelling	DS	SS	OMSI	ADHD	Phase-1[1]	Phase-2a[1]
PA											
Age	-0.082										
Reading	-0.053	0.031									
PWD	0.029	-0.212	.569**								
Spelling	-0.177	0.115	.394*	.401*							
DS	-0.222	0.129	0.091	0.010	0.257						
SS	0.037	-0.133	0.165	0.098	0.137	0.032					
OMSI	0.184	0.112	-0.002	0.041	-0.105	-0.243	-0.140				
ADHD	0.271	0.050	-0.087	-0.275	-0.155	-0.073	-0.222	-0.143			
Phase-1[1]	-0.098	0.291	-0.280	-0.313	-0.040	0.225	0.079	-0.131	-0.222		
Phase-2a[1]	0.204	-0.048	-0.257	-0.145	-0.172	-0.105	0.097	-0.055	0.023	0.344	
Phase2-b[1]	0.302	-0.130	0.069	0.063	0.083	0.049	-0.103	-0.044	0.076	-0.132	-0.298

*Correlation is significant at the 0.05 level (2-tailed); **Correlation is significant at the 0.001 level (2-tailed); N = 30; [1] HP-LP for POz

Table 18 Correlations: Behavioral scores on ASL for Atypical group

	PA	Age	Reading	PWD	Spelling	DS	SS	OMSI	ADHD	Phase 2a[1]
PA										
Age	0.190									
Reading	0.269	0.387								
PWD	-0.229	-0.329	0.426							
Spelling	0.266	0.394	.767**	0.061						
DS	-0.344	-0.024	0.469	0.344	0.488					
SS	-0.533	-0.207	0.517	.771**	0.158	.661*				
OMSI	-0.076	-0.438	-0.597	-0.254	-.663*	-0.159	-0.216			
ADHD	0.268	0.189	0.426	0.479	-0.012	0.304	0.355	-0.080		
Phase 2a[1]	-0.114	0.588	.706*	0.201	0.600	.634*	0.492	-.687*	0.457	
Phase 2b[1]	0.190	-0.079	0.092	-0.091	0.321	0.317	-0.079	0.413	-0.061	-0.212

*Correlation is significant at the 0.05 level (2-tailed); **Correlation is significant at the 0.01 level (2-tailed); N = 10; [1]LP - HP

Table 19 Correlations: ERP scores on AGL (500-700ms time window) for the Atypical group

	PA	Age	Reading	PWD	Spelling	DS	SS	OMSI	ADHD	Phase-1[1]	Phase-2a[1]
PA											
Age	-0.070										
Reading	0.018	0.325									
PWD	-0.263	-0.131	0.472								
Spelling	0.244	0.454	.550*	0.167							
DS	-0.420	0.408	0.505	0.356	0.281						
SS	-0.333	0.050	0.502	.626*	0.420	0.236					
OMSI	0.262	-0.313	-.630*	-0.222	-0.195	-0.319	-0.128				
ADHD	-0.053	0.357	0.431	0.380	0.142	0.380	0.360	-0.159			
Phase-1[1]	-0.244	0.296	0.294	0.088	0.196	.573*	-0.032	-0.257	0.083		
Phase-2a[1]	0.035	0.018	-0.088	-0.143	0.011	-0.068	0.106	0.073	-0.108	-0.093	
Phase2-b[1]	-0.140	0.343	.565*	0.366	0.507	0.349	0.447	-0.195	.542*	0.229	-.529*

*Correlation is significant at the 0.05 level (2-tailed); **Correlation is significant at the 0.001 level (2-tailed); *N* = 15; [1]HP-LP for POz