

# Cognitive Neural Mechanisms of Statistical Learning and Its Relationship with Language

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## Abstract

Statistical learning refers to the process by which individuals discover statistical regularities such as transitional probabilities within a continuous stimulus stream, first introduced in the classic infant speech segmentation study by Saffran et al. (1996). A substantial body of research has confirmed the ubiquitous nature of statistical learning, and recent scholarly attention has shifted toward investigating the specificity of statistical learning and its influence on cognition, particularly by explicating the cognitive neural mechanisms of statistical learning from both the learning process and its specificity, and revealing its interaction with language. Future research should adopt a multimodal brain-behavior data perspective, enrich the behavioral and neural indices of statistical learning outcomes, examine the dynamic neural activity patterns underlying different types of statistical learning processes, establish brain-behavior associations in statistical learning, deepen our understanding of the cognitive neural mechanisms of statistical learning, and based on the interaction between statistical learning and language, explore statistical learning intervention approaches that facilitate language learning by targeting adult second language acquisition and incorporating musical statistical learning training.

## Full Text

### Preamble

#### The Cognitive and Neural Mechanisms of Statistical Learning and Its Relationship with Language

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**Abstract:** Statistical learning (SL) refers to the process by which individuals discover statistical regularities such as transitional probabilities within continuous streams of stimuli, a concept first introduced in Saffran et al.'s (1996) seminal study on infant speech segmentation. While numerous studies have confirmed the ubiquitous nature of SL, recent research has begun to focus on its specificity and impact on cognition. In particular, investigations have explored the cognitive and neural mechanisms of SL from the perspectives of both learning processes and domain specificity, while also revealing its interactive relationship with language. Future research should adopt a multimodal data perspective encompassing both brain and behavioral measures, enrich the behavioral and neural indices of SL outcomes, examine the dynamic neural activity patterns underlying different types of SL processes, establish brain-behavior correlations in SL, and deepen our understanding of its cognitive and neural mechanisms. Building upon the interaction between SL and language, future studies should also examine SL-based interventions for language learning, particularly through adult second language acquisition and music-based SL training.

**Keywords:** statistical learning; transitional probability; specificity; language; multimodal data

Statistical learning (SL) is the process through which individuals gradually discover statistical regularities in continuous streams of external stimuli. Individual differences in SL reflect sensitivity to statistical structural information such as frequency and probability distributions, and SL exerts important influences on cognitive activities including language (Arnon, 2019; Erickson & Thiessen, 2015; Saffran & Kirkham, 2018; Thiessen, Kronstein, & Hufnagle, 2013; Wu & Deng, 2012). The concept of SL was first introduced in Saffran, Aslin, and Newport's (1996) classic study on auditory speech segmentation in 8-month-old infants. In this study, infants were presented with a 2-minute continuous speech stream composed of four trisyllabic nonsense words: *bidaku*, *padoti*, *golabu*, and *tupiro*. The results demonstrated that infants could perceive differences in transitional probability (TP) between syllables within the continuous speech stream, thereby exhibiting lexical segmentation ability.

TP, calculated as a conditional probability, is determined as follows: Assuming two syllables X and Y appear sequentially as XY, the probability of Y occurring given X (termed "forward TP") is  $P(Y|X) = P(XY)/P(X)$ , while the probability of X occurring given Y (termed "backward TP") is  $P(X|Y) = P(XY)/P(Y)$ . Here,  $P(XY)$  represents the frequency of XY co-occurrence in the entire stimulus sequence,  $P(X)$  represents the frequency of X, and  $P(Y)$  represents the frequency of Y. Unless otherwise specified, TP in SL research generally refers to forward TP. Consequently, TP between syllables within the same word is

necessarily higher than TP between syllables across word boundaries. If individuals can perceive these TP differences, they can achieve lexical segmentation and recognition (Aslin, Saffran, & Newport, 1998; Saffran, Aslin, & Newport, 1996). Sensitivity to TP has a neurophysiological basis; research has found that the amplitude of mismatch negativity (MMN) effectively reflects TP differences in auditory stimulus sequences (Fitzgerald & Todd, 2018; Koelsch, Busch, Jentschke, & Rohrmeier, 2016).

The classic SL paradigm comprises two phases: a stimulus familiarization phase and a learning outcome test phase. Using visual SL tasks as an example, the stimulus materials consist of 24 abstract black shapes (as shown in [Figure 1: see original paper]) that form 8 triplets. During the familiarization phase, participants view a 10-minute stream of visual shapes, with each shape presented for 200 ms followed by a 200 ms interval. The order of the 8 triplets is pseudo-random, with the same triplet never appearing consecutively. The sequential order within each triplet remains fixed, and each triplet repeats 75 times. Participants are instructed to attend to the shapes appearing sequentially at the center of the screen, but are not informed about the existence of triplets. In the test phase, participants complete 32 trials of a two-alternative forced-choice (2AFC) recognition test. In each trial, two triplets are presented sequentially: one is a target stimulus that appeared repeatedly during familiarization (TP = 1), while the other is a foil composed of three shapes from the 24-shape set that never appeared together during familiarization (TP = 0). Participants must judge which of the two triplets feels more familiar. Successful recognition of familiarized triplets from foils demonstrates that participants engaged in SL of the TP relationships between shapes during familiarization, with recognition accuracy serving as a crucial behavioral index of individual visual SL ability (Frost, Siegelman, Narkiss, & Afek, 2013). Batterink and Paller proposed that SL comprises at least two subcomponents related to perceptual and memory processing: perceptual grouping and memory storage/retrieval. In auditory SL of language, perceptual grouping primarily involves combining adjacent stimuli that repeatedly co-occur (e.g., syllables “tu” and “be” ) into a composite unit (e.g., the disyllabic word “tube”)—a process of lexical segmentation—while memory storage involves retaining these composites for later retrieval during the test phase (Batterink & Paller, 2017, 2019).

[Figure 1: see original paper] Visual statistical learning stimulus materials (adapted from Frost et al., 2013)

Traditional perspectives posit two external characteristics of the SL process: first, learners receive no external guidance during learning and are not informed about what to learn during familiarization; second, learners lack explicit awareness of the acquired statistical knowledge. While test performance can reveal whether learners have mastered the statistical regularities, even successful learners cannot explicitly report them. Researchers often associate SL with implicit learning, which refers to learning without external guidance and without explicit awareness of what has been learned, a concept first introduced by Reber

(1967) (Batterink, Reber, Neville, & Paller, 2015). Moreover, both SL and implicit learning involve statistical structural information such as sequences and probabilities, leading many researchers to directly term SL “implicit statistical learning” (Goujon, Didierjean, & Thorpe, 2015; Jost, Conway, Purdy, Walk, & Hendricks, 2015; Perkovic & Orquin, 2018). However, some researchers have questioned the validity of using the single behavioral criterion of “inability to explicitly report statistical regularities” to judge the characteristic of “lack of explicit awareness” in SL, arguing that this all-or-nothing metric may be overly simplistic and strict, potentially underestimating learners’ explicit knowledge. Using subjective confidence ratings for choices made during forced-choice tests as an external behavioral index of explicit SL knowledge, researchers have found that individuals’ subjective confidence in their test choices correlates significantly with their SL recognition performance (Batterink et al., 2015; Bertels, Franco, & Destrebecqz, 2012). Thus, even when individuals cannot report specific statistical regularities, this does not necessarily indicate a complete lack of explicit knowledge. Recent proposals suggest that while SL and implicit learning overlap, they emphasize different aspects: SL focuses more on learning content, such as statistical structural information like frequency and probability distributions, whereas implicit learning emphasizes learning characteristics, including whether knowledge representations take the form of abstract rules or exemplars and the degree of learners’ explicit awareness (Arnon, 2019). Clarifying the relative relationship between SL and implicit/explicit learning requires integration of cognitive and neuroscientific evidence regarding the SL process.

Since its introduction, subsequent research has confirmed the ubiquitous existence of SL across various cognitive domains (linguistic and non-linguistic), sensory modalities (visual and auditory), age groups (infants, children, and adults), populations (healthy individuals and those with autism spectrum disorder), and even species (humans and monkeys) (Arnon, 2019; Kirkham, Slemmer, & Johnson, 2002; Milne, Petkov, & Wilson, 2018; Monroy, Meyer, Schroer, Gerson, & Hunnius, 2019; Newport, 2016; Raviv & Arnon, 2018; Roser, Aslin, McKenzie, Zahra, & Fiser, 2015; Saffran & Kirkham, 2018; Santolin & Saffran, 2018; Schwab et al., 2016; Shufaniya & Arnon, 2018; Slone & Johnson, 2018; Tang et al., 2015). Early perspectives suggested that since infants already possess SL ability, it represents an early-maturing capacity that does not change significantly with age. For instance, research found no significant differences in auditory SL performance between 6-year-old children and adults (Saffran, Newport, Aslin, Tunick, & Barrueco, 1997). However, recent evidence supports the view that individual SL ability develops with age while being constrained by stimulus type and modality. While auditory SL of linguistic stimuli in children aged 5–12 appears unaffected by age, both visual SL and auditory SL of non-linguistic stimuli improve with age (Arciuli & Simpson, 2011; Raviv & Arnon, 2018; Shufaniya & Arnon, 2018). In recent years, researchers have begun investigating the specificity of different types of SL across domains, modalities, and individuals, as well as their roles in cognition such as language (Frost et al., 2015; Krogh, Vlach, & Johnson, 2012).

Recent research demonstrates significant individual differences in SL. Although group mean performance typically exceeds chance levels, the distribution of individual SL scores shows substantial variability, with approximately one-third of participants performing below chance (Arnon, 2019; Frost et al., 2015; Siegelman, Bogaerts, & Frost, 2017; Siegelman & Frost, 2015). A study examining auditory SL across young, middle-aged, and older adult groups found age-related decline in SL, which correlated with decreased working memory updating ability (Palmer, Hutson, & Mattys, 2018). Evidence from children's literacy skills (Spencer, Kaschak, Jones, & Lonigan, 2015), children's comprehension of passive sentences and object relative clauses (Kidd & Arciuli, 2016), and university students' processing of relative clauses (Misyak, Christiansen, & Tomblin, 2010) indicates that these individual differences in SL directly affect its role in language processing. These findings will be elaborated in the section on SL's role in language. Therefore, this review will focus on summarizing and analyzing new developments in two main areas: the cognitive and neural mechanisms of SL, and the relationship between SL and language, while proposing directions for future research.

## 2. Cognitive and Neural Mechanisms of Statistical Learning

Following extensive behavioral research confirming the ubiquitous nature of SL across domains, modalities, and populations, researchers have begun investigating its underlying cognitive and neural mechanisms, focusing primarily on the neural mechanisms of the SL process itself and the specificity of SL. These two aspects will be elaborated below.

### 2.1 Neural Mechanisms of the Statistical Learning Process

The complete SL process includes both the stimulus familiarization phase and the learning outcome test phase. In fact, the familiarization phase represents the truly "pure" online learning process, encompassing both perceptual grouping and memory storage, while the test phase primarily reflects memory retrieval. Cunillera and colleagues' ERP studies on auditory SL revealed that during familiarization, syllable triplets forming nonsense words elicited a significant N400-like negative component between 300-500 ms compared to non-word triplets, with amplitude decreasing as exposure time increased. The researchers identified this component as a neurophysiological marker of lexical segmentation. Subsequent fMRI research found significant activation in the posterior superior temporal gyrus and dorsal premotor cortex during lexical segmentation (Cunillera et al., 2009; Cunillera, Toro, Sebastian-Galles, & Rodriguez-Fornells, 2006). Batterink and Paller (2017) compared neural entrainment during familiarization between streams with consistent word-forming patterns and random streams, further revealing the neurophysiological patterns of perceptual grouping. Using Morlet wavelet transforms, they calculated a word learning index (WLI) as the ratio of inter-trial coherence (ITC) at word frequency to ITC at syllable frequency. Re-

sults showed that WLI was greater for structured streams than random streams, with this difference increasing as stimulus familiarity grew. Moreover, EEG WLI during familiarization predicted behavioral performance in the lexical learning test phase. Additionally, Batterink and Paller (2019) employed a visual cross-modal interference task to compare neural entrainment differences in auditory SL with and without interference, finding no significant differences between conditions. This suggests that perceptual grouping does not require intentional attention. However, based on current findings, it remains difficult to dissociate the perceptual grouping and storage sub-processes. Future research should integrate multimodal neural data to further clarify their relationship and identify evidence for their temporal or spatial dissociation.

Furthermore, previous research on the test phase has primarily focused on offline recognition accuracy while neglecting the online recognition process itself. Inferences about SL effectiveness are based on whether learners show differential responses to stimuli with different TPs during testing, suggesting they mastered the statistical structure during familiarization. These differential responses should be evident not only in offline behavioral indices like recognizing familiarized triplets among foils but also in neural activity patterns during the recognition process. Research shows that compared to foils, target triplets presented during recognition elicit a larger late positive component (LPC) between 700–1000 ms. Further comparisons of reaction times and P300 amplitudes when recognizing syllables at different positions within target triplets reveal that, due to priming effects, later syllables are recognized more quickly and elicit smaller P300 effects between 400–800 ms, as stimuli with higher probability and predictability produce smaller P300 responses (Batterink, 2017; Batterink et al., 2015).

Moreover, previous examinations of explicit knowledge in SL during the test phase have relied primarily on offline probability estimation of triplet occurrence, potentially underestimating the contribution of explicit learning while overestimating implicit learning. Research indicates that the implicit learning/memory system primarily depends on basal ganglia nuclei such as the striatum, whereas the explicit learning/memory system relies mainly on medial temporal lobe (MTL) structures like the hippocampus (Knowlton, Mangels, & Squire, 1996; Squire, Stark, & Clark, 2004). Consequently, researchers have investigated the dynamic involvement of explicit and implicit learning systems during different types of SL by examining activation and connectivity patterns in these brain regions, revealing that different types of SL involve distinct contributions from the two systems (Batterink, Paller, & Reber, 2019; Sawi & Rueckl, 2018). Using sleep monitoring and fMRI, researchers examined the impact of sleep on auditory tonal SL, finding that test performance after a 24-hour interval with sleep was superior to performance after only a 30-minute interval. Furthermore, the amount of slow-wave sleep effectively predicted SL performance and brain activation patterns. After sleep, connectivity between the striatum and parahippocampal gyrus decreased while connectivity between the putamen and planum temporale increased, suggesting that SL involves a gradual transfer from hip-

pocampal to striatal memory systems and that sleep facilitates this transfer (Durrant, Cairney, & Lewis, 2013). Thus, SL is not governed by a uniform implicit learning/memory system; rather, the involvement of explicit and implicit learning systems changes dynamically throughout the SL process, with the specific type of SL modulating this transition.

## 2.2 Neural Mechanisms of Statistical Learning Specificity

Despite evidence for the ubiquitous nature of SL, recent research has begun examining the neural mechanisms underlying its specificity—that is, how different types of SL in different domains, modalities, and individuals exhibit neural distinctiveness. Regarding domain specificity, neural activity patterns differ when the brain processes statistical information from different domains. The medial temporal lobe plays an important role in extracting temporal statistical rules (Schapiro, Gregory, Landau, McCloskey, & Turk-Browne, 2014), whereas during category learning based on auditory statistical regularities, the posterior striatum shows sensitivity to stimulus statistical structure, with connectivity strength between this region and the left superior temporal sulcus correlating with offline category learning performance (Lim, Fiez, & Holt, 2019). ERP research on infant face recognition found that 6.5-month-old infants can engage in SL based on bimodal but not unimodal frequency distribution information (Altvater-Mackensen, Jessen, & Grossmann, 2017). Monroy and colleagues' series of EEG and eye-tracking studies demonstrated that infants can extract statistical regularities from continuous action sequences to generate action predictions, which are reflected in their eye movement patterns (Monroy, Gerson, & Hunnius, 2017). When actions violate these predictions during testing, a negative potential is elicited at midline electrodes between 250–750 ms (Monroy, Gerson, Dominguez-Martinez, et al., 2019), and frequency-domain analysis reveals that predicted actions are accompanied by suppression of mu rhythm (7–9 Hz) (Monroy et al., 2019).

Regarding modality specificity, visual and auditory SL may show different patterns of cerebral lateralization, which may constrain how SL influences language and other cognitive functions (Karuza et al., 2013; Qi, Sanchez Araujo, Georgian, Gabrieli, & Arciuli, 2018; Roser, Fiser, Aslin, & Gazzaniga, 2011). Roser et al. (2011) compared learning performance between split-brain patients and control groups in a visual SL task presented to left and right visual fields, providing evidence for right hemisphere dominance in visual SL. Karuza et al. (2013) used fMRI to examine neural activity patterns during an auditory word segmentation task, finding significant correlations between activation in left inferior frontal gyrus and SL performance. Qi et al. (2018) further compared how auditory versus visual SL differentially influences reading development in children and adults, finding that auditory SL had a greater impact on reading development, possibly due to the left lateralization of language brain regions involved in auditory SL. However, future research is needed to confirm the relationship between modality-specific neural mechanisms of SL and the neural specificity of language

and other cognitive functions.

Regarding individual specificity, while substantial behavioral research demonstrates significant individual differences in SL, the neural mechanisms underlying these differences remain unclear. Some researchers compared P300 indices during the test phase of visual SL across adult, 9-12-year-old, and 6-9-year-old groups, finding no significant differences and interpreting this as neurophysiological evidence for developmental invariance in SL (Jost et al., 2015). Conversely, other researchers argue for neural specificity in SL across individuals. Using structural MRI (sMRI), investigators examined relationships between cortical thickness in three regions of interest (left inferior frontal cortex, hippocampus, and caudate nucleus) and SL performance in children aged 5-8.5 years. Results showed that left inferior frontal cortex thickness and right hippocampal volume predicted SL performance. Although thickness and volume in these regions did not change with age, older children showed stronger predictive relationships between right hippocampus and SL (Finn, Kharitonova, Holtby, & Sheridan, 2019). Additionally, children with autism spectrum disorder exhibited weaker N1 and P300 effects during visual SL compared to typically developing children, with N1 amplitude correlating with nonverbal IQ scores and P300 amplitude correlating with social adaptive functioning (Jeste et al., 2015).

### 3. The Relationship Between Statistical Learning and Language

The concept of SL originated from classic infant speech segmentation studies. Early research focused on SL's influence on language acquisition, while recent work has begun examining their bidirectional interaction. Building upon a deeper investigation of SL's specific roles in different language learning domains, researchers are now exploring how linguistic experience (native and bilingual) influences SL.

#### 3.1 The Role of Statistical Learning in Language

Research on SL's influence on language has expanded in two main directions: examining its impact on linguistic tasks beyond speech processing, and investigating its role in second language (L2) learning. SL's role in language was initially established in speech and lexical recognition, with subsequent research confirming its involvement in more complex linguistic tasks such as grammar, spelling, and reading (Elleman, Steacy, & Compton, 2019; Treiman, Kessler, Boland, Clocksin, & Chen, 2018). University students can learn content words in artificial grammars based on distributional statistical information, and comparisons between young adults (around 20 years) and older adults (over 70 years) show that while older adults can also learn grammatical categories from statistical information, their performance is poorer than that of younger adults (Schwab et al., 2016). Furthermore, individual differences in SL ability effectively predict performance in relative clause comprehension (Misyak et al., 2010). The correla-

tion between SL and reading achievement has been confirmed in both child and adult populations, with SL ability serving as an important predictor of reading performance (Arciuli & Simpson, 2012). Structural equation modeling has also revealed SL' s predictive role in early literacy skills in young children (Spencer et al., 2015). ERP and fMRI studies showing similar neural patterns between SL and language processing provide supporting evidence for the neural basis of SL' s role in language (Christiansen, Conway, & Onnis, 2012; Petersson, Folia, & Hagoort, 2012).

Moreover, SL' s role in language learning has been further confirmed in populations with developmental language disorders (Saffran, 2018). For example, university students with dyslexia perform above chance on auditory SL tasks but significantly worse than typical controls, indicating a general SL deficit in dyslexia (Gabay, Thiessen, & Holt, 2015). A meta-analysis comparing auditory linguistic SL between individuals with and without developmental language disorder (DLD) found clear SL deficits in those with DLD, further confirming SL' s role in language learning (Lammertink, Boersma, Wijnen, & Rispens, 2017). Additionally, deaf children with cochlear implants who experience early language deprivation show poorer SL performance than hearing children, and those deaf children with better SL scores demonstrate greater language improvement after implantation (Conway, Pisoni, Anaya, Karpicke, & Henning, 2011).

Beyond these findings, researchers have begun investigating how individual SL ability influences L2 learning, primarily because L2 learning exhibits specificity distinct from native language acquisition. Language characteristics and age of acquisition are two important variables affecting language learning. In native language research, these factors can be examined separately—for example, by comparing behavioral and neural commonalities and differences across native speakers with dyslexia to investigate language characteristics (D' Mello & Gabrieli, 2018; Hu et al., 2010; Siok, Perfetti, Jin, & Tan, 2004), or by comparing learners who began acquiring their native language at different ages to examine age-of-acquisition effects, particularly before and after the critical period. Adult late-literates and illiterates provide excellent models for such research (Carreiras et al., 2009; Dehaene, Cohen, Morais, & Kolinsky, 2015). Comparisons of brain structure among former Colombian guerrilla members who became literate as adults, illiterate adults, and adults who learned to read in childhood revealed that literate adults had greater white matter in the splenium of the corpus callosum and greater gray matter in bilateral angular gyri, dorsal occipital gyri, middle temporal gyri, left supramarginal gyrus, and left superior temporal gyrus compared to illiterates. Furthermore, compared to those who learned to read in childhood, adult late-literates showed greater white matter in corpus callosum regions connecting bilateral angular and dorsal occipital gyri (Carreiras et al., 2009).

However, these two factors become more complex and difficult to disentangle in L2 learning research. First, native and L2 learning interact, requiring simultaneous consideration of characteristics of both languages. Different types

of L2 learners vary in the degree of difference between their native and target languages (de Bruin, 2019), meaning that SL' s influence on native language learning cannot be directly generalized to L2 learning, especially when the languages differ substantially. Second, even when learners share the same native and target languages, the age at which they begin L2 learning affects the cognitive and neural mechanisms of L2 acquisition (Das, Padakannaya, Pugh, & Singh, 2011). Additionally, compared to native language learning, L2 learners show greater variability in age of onset, and while post-critical-period native language learners are rare (particularly for spoken language), post-critical-period L2 learners are common. In today' s globalized world with increasing multi-lingual demands, the number of adult foreign language learners continues to grow (Cores-Bilbao, Fernandez-Corbacho, Machancoses, & Fonseca-Mora, 2019; Kramsch, 2014). Therefore, investigating SL' s influence on L2 learning holds important theoretical and practical significance.

Research on SL' s influence on non-native language processing in infants has primarily examined how monolingual infants under 2 years process non-native linguistic stimuli. Studies show that infants can also engage in SL of non-native language stimuli, but undergo an important transition around 12 months from cross-linguistic universality to native-language specificity. Infants can learn sound-meaning associations based on statistical cues in non-native stimuli (Hay, Pelucchi, Estes, & Saffran, 2011). Kuhl and colleagues' research demonstrates that infant language acquisition is highly plastic, with the ability to learn new languages declining rapidly with age. Initially, infants possess cross-linguistic universal SL abilities: English-learning infants aged 6-8 months can show the same phonetic discrimination ability as Mandarin-learning infants after brief exposure to Mandarin phonetic contrasts /t / and / /. However, infants gradually become more sensitive to statistical information in their native language, showing enhanced discrimination of native phonetic contrasts and reduced discrimination of non-native contrasts. The critical transition period occurs at 8-10 months, with sensitivity to non-native speech sounds declining by 10-12 months (Kuhl, 2004; Kuhl, Tsao, & Liu, 2003). Recent research on non-native Mandarin tone perception in 88 Dutch infants at 5, 11, and 14 months found that infants' ability to discriminate non-native tones declined with increasing age (Liu & Kager, 2017).

In contrast, research on SL' s influence on adult L2 learning remains relatively scarce, with most evidence coming from visual SL studies. Frost et al. (2013) pioneered this area by using a visual SL task to examine the relationship between individual SL ability and Hebrew L2 literacy skills in native English-speaking adult learners. They found that L2 learners with better visual SL ability were better able to master Semitic morphological structures in Hebrew words. Additionally, Wu and colleagues compared brain activation patterns during pseudo-phonogram orthography-to-phonology conversion tasks between native Chinese speakers and Chinese L2 learners, calculating correlations between visual SL performance and activation in six regions of interest involved in orthography-to-phonology processing. Results showed that native Chinese speakers' visual SL

performance correlated negatively with activation in left inferior parietal lobule, while Chinese L2 learners' performance correlated negatively with activation in left inferior frontal gyrus, demonstrating that individual SL ability is closely related to orthography-to-phonology conversion processes in word recognition (Yu et al., 2019).

### 3.2 The Influence of Language Experience on Statistical Learning

Compared to extensive research on SL's influence on language, studies examining how language experience affects SL remain scarce. These studies primarily investigate the impact of native language experience and bilingual experience on SL. First, SL in speakers of different native languages exhibits language-specific patterns influenced by their language's structural characteristics. English and Korean employ different word order structures: head-initial (e.g., "in Sapporo") in English and head-final (e.g., "Sapporo in") in Korean. This results in lower forward TP and higher backward TP in English (since many words can follow "in" but few can precede "Sapporo"), with the opposite pattern in Korean. Researchers examined how these different word order structures affect auditory linguistic SL (nonsense syllables), visual non-linguistic SL (abstract shapes), and auditory non-linguistic SL (pure tones) in adult native speakers. Results showed that language characteristics constrain individuals' SL preferences: native Korean speakers were more sensitive to forward TP, while native English speakers were more sensitive to backward TP, with this preference appearing only in linguistic SL (Onnis & Thiessen, 2013). Further comparisons of auditory SL characteristics in English and Korean infants at different ages revealed that 7-month-old English infants showed no TP direction preference, but 13-month-old English infants exhibited the same backward TP preference as English adults. These findings suggest that individual SL preferences develop gradually under the influence of native language experience (Thiessen, Onnis, Hong, & Lee, 2019).

Second, bilingual experience facilitates SL of linguistic stimuli. One study compared four groups of adults—English monolinguals, Chinese monolinguals, Chinese-English bilinguals, and bilinguals speaking English and a non-tonal language (Korean, Spanish, German, French, etc.)—on an artificial tonal language SL task to examine how prior linguistic experience (native language and bilingualism) affects subsequent learning. Results showed that Chinese monolinguals performed above chance but not significantly differently from English monolinguals, while both bilingual groups performed significantly above chance and better than the two monolingual groups. This suggests that while native tonal language experience does not significantly facilitate learning a new tonal language, bilingual experience—regardless of whether it includes a tonal language—enhances learning of a new artificial tonal language (Wang & Saffran, 2014). A subsequent longitudinal study confirmed the role of bilingual experience in SL of new linguistic stimuli. Researchers compared Chinese beginners whose native language was non-tonal before and after six months of Chinese learning,

examining changes in performance on auditory tonal SL and visual SL tasks compared to a control group. Both groups showed significant improvement in visual SL after six months, but only the Chinese learning group showed significant improvement in auditory SL (Potter, Wang, & Saffran, 2017).

Additionally, comparative studies of bilingual and monolingual infants further support the facilitative effect of bilingual experience on linguistic SL. By comparing 14-month-old infants' ability to use syllable transitional probabilities for word segmentation in two artificial languages, researchers found that monolingual infants could engage in SL and show word segmentation when exposed to a single language stream, but when two artificial language streams were presented alternately, only bilingual infants could complete word segmentation for both languages based on their respective statistical regularities (Antovich & Estes, 2018). However, recent research has questioned the facilitative effect of bilingual experience on SL. One study comparing English monolinguals, Spanish-Catalan bilinguals, and Spanish-English bilinguals on a visual shape SL task containing two statistical regularities found that all three groups could discover both regularities with no significant performance differences, leading the authors to conclude that bilingual experience does not significantly enhance SL (Bulgarelli, Bosch, & Weiss, 2019). Comparing these studies suggests that bilingual experience's facilitative effect appears primarily in auditory linguistic SL rather than visual non-linguistic SL. Therefore, the influence of bilingual experience on SL may be constrained by domain or modality, and future research should further investigate the factors that moderate this influence and their underlying cognitive and neural mechanisms.

#### 4. Future Directions in Statistical Learning Research

Despite extensive confirmation of SL's ubiquitous nature, our understanding of its underlying cognitive and neural mechanisms remains limited (Sawi & Rueckl, 2018). Future research should integrate multimodal data across brain and behavioral levels to investigate the cognitive and neural mechanisms of SL itself and its interaction with cognitive activities such as language, thereby better serving the international demand for foreign language learning in today's globalized world.

##### 4.1 Statistical Learning from a Multimodal Data Perspective

Previous SL research has focused primarily on confirming its ubiquitous nature and exploring its specificity, relying heavily on recognition accuracy in the test phase as a single index while relatively neglecting the familiarization phase. However, the truly "pure" learning process occurs during familiarization, when individuals gradually master the statistical structure of stimuli. Future research should investigate this dynamic process and its changing neural activity patterns from two main perspectives.

First, beyond offline evaluation, researchers should enrich online assessment

methods for both learning outcomes and learners' explicit knowledge during the test phase. For evaluating learning outcomes, in addition to the classic overall recognition accuracy for triplets, future studies could examine neural activity patterns during triplet recognition and behavioral and neural patterns of local processing for stimuli at different positions within triplets (Batterink et al., 2015). For offline evaluation of explicit knowledge, beyond overall subjective confidence ratings after testing, participants could rate each individual test trial (Batterink et al., 2015; Bertels et al., 2012). Batterink et al. (2015) required participants to classify each test trial choice into three categories: "remember" (confident memory-based selection), "familiar" (one option feels more familiar but without specific memory), or "guess" (random selection). Results showed significant differences in recognition accuracy across these three conditions, with performance in the "guess" condition not differing from chance. Additionally, researchers could infer explicit knowledge from dynamic changes in neural indices of implicit and explicit learning systems during testing, which is particularly important for studying the neural mechanisms of SL in special populations such as infants, individuals with autism, or even monkeys, who cannot provide external explicit knowledge reports (Finn et al., 2019).

Second, in the absence of external behavioral measures, future research should integrate multimodal brain data—including fMRI, sMRI, ERP, DTI, and MEG—to reveal dynamic changes during the familiarization phase. This approach could include three aspects: (1) Comparing neural patterns across different stages of familiarization to reveal dynamic changes in online learning, such as using MEG to show that revising learned statistical knowledge requires more time than learning new statistical knowledge (Daikoku, Yatomi, & Yumoto, 2017). (2) Establishing direct links between neural indices during online learning and learning outcomes in the test phase, such as correlations between connectivity strength of dorsal auditory and premotor cortices during the second learning phase and auditory lexical learning performance (Lopez-Barroso et al., 2015), activation in left inferior frontal gyrus and SL performance (Karuza et al., 2013), and event-related potentials between 500-1000 ms during visual SL and grammatical judgment reaction times (Daltrozzo et al., 2017). (3) Examining relationships between neural involvement of implicit and explicit learning systems during online learning and explicit cognitive evaluation results in the test phase, such as the gradual transfer from hippocampal to striatal memory systems during SL (Durrant et al., 2013) and relationships between brain structure in implicit and explicit memory regions and SL performance (Finn et al., 2019). Based on these investigations, comparing dynamic learning processes across different types of SL in different individuals, domains, and modalities will enhance understanding of SL specificity and further enrich the cognitive and neural mechanisms of SL.

## 4.2 The Role of Statistical Learning in Adult Second Language Learning

Current globalization demands greater multilingual competence from adults. We propose that an important future direction for SL research is to reveal its unique mechanisms in adult L2 learning to facilitate language acquisition. Research in this area remains in its preliminary stages, and future studies should integrate multimodal data to further confirm the cognitive mechanisms and neural basis through which SL influences adult L2 learning.

First, not all bilinguals are equivalent; individual differences in linguistic experience and cognitive abilities constrain SL's role in L2 learning. A key question is how to enhance learners' sensitivity to statistical regularities in different types of L2 stimuli under these constraints, particularly when the L2 differs substantially from the native language. Bilingualism research requires detailed description and assessment of bilinguals' linguistic experience and individual differences in cognitive factors including SL, cognitive control, working memory, and intelligence (de Bruin, 2019; Hung et al., 2019; Kuo et al., 2015). Reading provides a clear example: its neural mechanisms are influenced by language characteristics and age of acquisition. Due to different degrees of orthography-to-phonology and orthography-to-semantics mappings in alphabetic and logographic scripts, English readers with dyslexia show atypical activation in left temporoparietal regions, while Chinese readers with dyslexia show structural and functional abnormalities in left middle frontal gyrus, though whether they also show atypical temporoparietal activation remains debated (D' Mello & Gabrieli, 2018; Hu et al., 2010; Siok et al., 2004). Even among alphabetic scripts, orthographic transparency varies: reading transparent scripts like Italian and Hindi enhances activation in dorsal pathways involved in phonological processing, while reading less transparent scripts like English enhances activation in ventral pathways involved in semantic processing. For Hindi-English bilinguals, differences in neural activity patterns when reading Hindi versus English relate to English learning duration (Das et al., 2011). Therefore, when native and target languages belong to different writing systems (logographic vs. alphabetic) or differ in tonal characteristics, native language transfer may cause L2 learners to show different sensitivity to statistical regularities in various types of visual and auditory SL, thereby affecting SL's role in L2 learning. Additionally, what is the relationship between individual differences in different types of SL abilities across different stimuli and modalities and various language skills (listening, speaking, reading, writing)? How much variance in L2 learning outcomes can be uniquely explained by SL ability compared to other cognitive factors such as intelligence, cognitive control, and working memory? These are questions that future research must address.

Second, existing research demonstrates that adult L2 learning has important neurobiological underpinnings (Kuhl et al., 2016; Mamiya, Richards, Coe, Eichler, & Kuhl, 2016). Mamiya et al. (2016) used DTI to track white matter structural changes in Chinese university students studying in the United States

before and after an English language course. They found that longer course participation was associated with higher fractional anisotropy (FA) and lower radial diffusivity (RD) in the right superior longitudinal fasciculus. Furthermore, individuals' catechol-O-methyltransferase (COMT) genotype modulated the relationship between L2 learning duration and white matter changes, with COMT genotype and FA together explaining substantial variance in language course performance. Similarly, Kuhl et al. (2016) used DTI to examine relationships between white matter structure and duration of residence and English use in adult Spanish-English bilinguals living in the United States. They found that FA in left inferior fronto-occipital fasciculus correlated positively with years of residence in the U.S. and years of speaking English, while RD in this region correlated negatively with years of residence and years of listening to English. What role does SL play in these brain structural changes that accompany L2 learning? What are the brain-behavior relationships between SL and adult L2 learning, and how do these relationships dynamically change across different types of L2 learners and different stages of L2 acquisition? These are also critical questions for future research.

Finally, SL is a capacity with plasticity that is constrained by factors such as age, modality, and stimulus type. Future research should identify effective factors for promoting SL and design targeted intervention protocols for different populations with different language needs to enhance language learning and other cognitive abilities (Deocampo, Smith, Kronenberger, Pisoni, & Conway, 2018). SL interventions aim to improve relevant cognitive abilities by enhancing sensitivity to statistical structural information. Intervention approaches could consider both direct and indirect methods. Direct interventions might design SL materials and presentation methods based on individual SL preferences. Research shows that bimodal distribution information facilitates infant SL of speech sounds and faces more effectively than unimodal distribution (Altwater-Mackensen et al., 2017; Song & Meng, 2012), and that secondary cross-modal cues consistent with stimulus statistical regularities can effectively enhance SL. For instance, when visual shape-color associations are consistent with auditory speech statistical regularities, auditory SL performance improves (Forest, Lichtenfeld, Alvarez, & Finn, 2019). Therefore, future research could combine language information distribution characteristics with audiovisual integration to explore optimal combinations for promoting linguistic SL in different populations. Indirect interventions could employ cross-domain music training to enhance linguistic SL. Research shows that music training improves general auditory recognition and prediction abilities, thereby facilitating linguistic SL (Francois, Chobert, Besson, & Schon, 2013; Francois & Schon, 2011; Zhao & Kuhl, 2016). ERP studies found that adult musicians with over 12 years of professional training showed better auditory SL performance in a new artificial language compared to non-musicians (Francois & Schon, 2011). A two-year longitudinal study of 8-year-old children receiving music training revealed that trained children showed better speech segmentation ability in both behavioral and EEG measures (Francois et al., 2013). Zhao and Kuhl (2016) further used

MEG in an oddball paradigm to examine music training's effects on music and speech processing in 9-month-old infants, finding that music- and speech-deviant stimuli elicited larger mismatch responses (MMR) in auditory and prefrontal cortices of musically trained infants compared to controls. Future research should further examine how traditional music training promotes speech SL and investigate its underlying cognitive and neural mechanisms to establish optimal music training protocols for language learning, including training format and duration. Additionally, direct comparisons of SL training using speech versus music materials across different populations could test the applicability of different SL training approaches.

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*Note: Figure translations are in progress. See original paper for figures.*

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