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The multi-component nature of statistical learning

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The central argument presented in this paper is that statistical learning (SL) is an ability comprised of multiple components that operate largely implicitly. Components relating to the stimulus encoding, retention and abstraction required for SL may include, but are not limited to, certain types of attention, processing speed and memory. It is likely that individuals vary in terms of the efficiency of these underlying components, and in patterns of connectivity among these components, and that SL tasks differ from one another in how they draw on certain underlying components more than others. This theoretical framework is of value because it can assist in gaining a clearer understanding of how SL is linked with individual differences in complex mental activities such as language processing. Variability in language processing across individuals is of central concern to researchers interested in child development, including those interested in neurodevelopmental disorders where language can be affected such as autism spectrum disorders (ASD). This paper discusses the link between SL and individual differences in language processing in the context of age-related changes in SL during infancy and childhood, and whether SL is affected in ASD. Viewing SL as a multi-component ability may help to explain divergent findings from previous empirical research in these areas and guide the design of future studies.

This article is part of the themed issue 'New frontiers for statistical learning in the cognitive sciences'.

1. Introduction

Statistical learning (SL) refers to the brain's ability to detect statistical regularities in the environment. SL operates in a number of ways, including the detection of relationships within scenes and spatial arrays, and within sequentially presented stimuli. When it comes to linguistic stimuli that are presented sequentially in the auditory modality, such as individual syllables presented as a continuous stream of pseudospeech or natural speech, detection of regularities has been referred to as word segmentation and speech segmentation. More broadly, detection of regularities within sequentially presented stimuli, usually in the auditory or visual modality, has been described as sequence learning, grammar learning and artificial grammar learning. This learning has been assessed using a variety of tasks, some of the most common being the embedded triplet task and serial reaction time tasks. For sequentially presented stimuli, the regularities have often been described as transitional probabilities but other terms such as probabilistic cues, dependencies (both adjacent and non-adjacent) and co-occurrences have also been used. Discussion about precisely how these kinds of regularities are computed has included mention of forward transitional probabilities, backward transitional probabilities and chunks (e.g. [1–5]). For further discussion on how regularities might be computed see also [6,7].

There has been debate about whether SL is implicit. Perruchet & Pacton argued that many commonly used tasks of SL fall under the umbrella of implicit learning because 'participants in SL experiments are faced with structured material without being instructed to learn. They learn merely from exposure to positive instances, without engaging in analytical processes or hypothesis-testing strategies.' [8, p. 233]. Even so, there is evidence that participants can develop some explicit knowledge of regularities during some SL experiments. This has led to the proposal

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that dissociable implicit and explicit forms of knowledge can sometimes accrue in parallel during SL (e.g. [9–11]). Although investigations are ongoing, there is substantial evidence that SL can operate largely implicitly even though certain SL tasks can be modified in ways that result in more or less explicit knowledge; for example, via task instructions (e.g. [12–14]). This paper focuses on SL as a largely implicit process.

It is thought that SL has a role to play during a range of complex mental activities including language processing, object recognition and music appreciation—and that SL is critical to understanding individual differences in these activities (e.g. [15–17]). The bulk of research effort examining whether SL is related to individual differences in mental activity has focused specifically on the link between SL and language processing (see recent reviews by Erickson & Thiessen [16] and Arciuli & von Koss Torkildsen [18]). This link is of central concern in this paper.

With regard to this link, there have been some inconsistent findings but there is growing evidence of an association between SL and many different aspects of language proficiency such as vocabulary, processing of grammatical structures and reading ability (e.g. [19–28]). Better performance on independent tasks of SL tends to be associated with greater language proficiency. As all of these studies reflect assessments undertaken at a single point in time or over a short period of time, further research is needed to explore questions of causality. Specifically, there is a need for more longitudinal research (as argued by Arciuli & von Koss Torkildsen [18] and investigated in only a handful of empirical studies such as Ellis *et al.* [29] and Shafto *et al.* [30]). In addition, we need more research that explores causality via training studies (e.g. [31–34]).

The central argument that I present in this paper is that SL is a multi-component ability. Components relating to the encoding, retention and abstraction of statistical regularities may include, but are not limited to, certain types of attention, processing speed and memory. It seems reasonable to hypothesize that individuals vary in terms of these underlying components, and in connectivity among these components, and that SL tasks differ in how they draw on particular underlying components. Viewing SL as a multi-component ability may lead to a deeper understanding of the nature of SL, and of the link between SL and individual differences in complex mental activities such as language processing. For a more comprehensive theory of SL, and for practical reasons relating to innovations in the remediation of language difficulties, it is important to understand how variability in language processing across individuals might relate to the different components that underpin SL.

In this paper, I will discuss how individual differences in language processing might relate to the multi-component nature of SL by focusing on language in the context of (i) age-related changes during infancy and childhood and (ii) neurodevelopmental disorders such as autism spectrum disorders (ASD) where language can develop atypically. Note that throughout this paper the terms autism and ASD are used interchangeably. The purpose of discussing SL in the context of age-related changes and autism is not to provide a systematic review of every study that has been undertaken in these areas. Rather, the aim is to outline some key SL studies that demonstrate divergent findings that extend beyond obvious methodological differences and thereby serve to demonstrate that SL may be comprised of multiple components.

2. Age-related changes in statistical learning

If we adhere to the view that first language acquisition is generally accomplished in early childhood, we might speculate that the capacity for SL ought to be at its peak during early childhood. Indeed, the prevailing view for many years was that implicit learning, unlike explicit learning, is underpinned by phylogenetically older brain structures that mature early and thereafter remain developmentally invariant (e.g. [35]). In line with this view, two seminal studies reported no effect of age on SL. These results were reported by Saffran *et al.*, who examined auditory SL in 6–7 year olds versus young adults [36] and Kirkham *et al.*, who examined visual SL in three groups of infants under 1 year of age [37]).

In contrast with these earlier studies, more recent studies have reported age-related effects in SL. For example, one study reported differences in sequence learning using a visual serial reaction time task in a group of children (mean age = 9.6 years) versus a group of adults (mean age = 27.9 years) [38]. In that study, behavioural data revealed that learning that was faster and more accurate in adults and fMRI data revealed a number of differences between the groups. Additionally, several studies have reported age-related changes in infants using tasks that assess the learning of visually presented sequences [39–41] and visual spatio-temporal sequences [42]. See also the review article by Krogh *et al.* [43].

In one of the largest studies conducted to date, Arciuli & Simpson examined the effect of age on visual SL in typically developing children aged 5–12 years ($n = 183$) using one of the most common paradigms in SL research, the embedded triplet paradigm [44]. The familiarization stream was comprised of individually presented cartoon figures that could be loosely described as aliens (these figures were not recognizable or readily verbalizable). Unbeknown to participants, there were regularities in the familiarization stream because the figures appeared in triplets. The familiarization phase was followed by a surprise test phase, which included 64 untimed alternative-forced-choice trials (2AFC: embedded triplets that occurred during familiarization pitted against foil triplets that never appeared during familiarization). Analyses revealed that age was a significant predictor of SL, with older children out-performing younger children. It was argued that the result was not due to age-related effects of overt attention during the task (indeed, researchers collected a measure of overt attention during familiarization via a cover task and included this variable as a predictor in the regression analysis). Rather, Arciuli & Simpson speculated that SL may be a multi-component capacity whereby some components mature earlier than others. They speculated that an implicit form of working memory (WM) may be an underlying component of SL and may be late maturing. This point about implicit working memory being a component of SL is taken up later in this paper.

In a study of children with and without autism, which is discussed more fully in the next section on autism, Jeste and co-workers investigated the effect of age on SL [45]. Event-related potentials (ERPs) were collected during a visual SL task with sequentially presented stimuli (individually presented coloured geometric shapes, such as a pink diamond and a yellow circle, that were easily verbalizable) that was administered to 45 children with ASD (2–6 years) and 23 age-matched control participants. The nature of the statistical regularity was that shapes appeared in pairs. Collapsed across groups, the data revealed a negative relationship between age and both N1 amplitude and Nc amplitude, which was interpreted as more robust learning in younger children. This finding is in contrast with that reported by Arciuli & Simpson [44], who found better learning in older children.

The studies by Arciuli & Simpson [44] and Jeste *et al.* [45] covered a broader age range than many previous studies, yet they reported opposing developmental trajectories. There are several key differences between these studies that are worthy of consideration. First, the two studies examined different ages; Arciuli & Simpson examined 5–12 year olds whereas Jeste *et al.* examined 2–6 year olds. Second, the task used by Jeste *et al.* contained embedded pairs while the task used by Arciuli & Simpson contained embedded triplets. While embedded triplets also contain embedded pairs, it is possible that statistical regularities that extended over a longer string of stimuli in the task used by Arciuli & Simpson may have placed greater demands on implicit WM. Third, although the age-related effect reported by Jeste *et al.* did not appear to be related to overt attention during the task, the researchers suggested that their task may not have been engaging for older children. This lack of engagement may have led to the appearance of less robust learning in older children in the ERP data even though this was not actually the case. Arciuli & Simpson found that age was a significant predictor of SL, even after overt attention was taken into consideration. Finally, the visual stimuli used in these two studies may have involved differences in encoding and retention. Given that the stimuli were recognizable geometric shapes, with each shape being presented in a particular colour in the study by Jeste *et al.*, there may have been a higher proportion of explicit processing relative to implicit processing during the SL task. By contrast, the stimuli used by Arciuli & Simpson were unfamiliar to children. Each alien figure contained a number of featural characteristics and did not have a recognizable geometric shape or defining colour. Thus, the stimuli in the SL task used by Arciuli & Simpson may have drawn more heavily on implicit encoding and retention. Of course, it could be argued that if an SL task involves more explicit processing relative to implicit processing, older children would be expected to show greater learning than younger children (i.e. the opposite of what Jeste *et al.* found). Unfortunately, it is difficult to speculate further on this point because the older children in the study by Jeste *et al.* may have lacked engagement with the task.

On balance, the empirical research reviewed here suggests that SL is not age-invariant. However, there are mixed findings concerning whether SL improves or deteriorates with age. How does this fit with our understanding of how SL supports first language acquisition? As mentioned earlier, if we believe that the task of first language acquisition is typically accomplished in early childhood, we might speculate that the capacity for SL would be at its peak during early childhood. Alternatively, in accordance with the view that language proficiency continues to improve beyond early childhood [46], we might expect that SL improves with age. See also Newport's 'Less is More' hypothesis, which rests on the somewhat paradoxical notion that 'the very limitations of the young child's information processing abilities provide the basis on which successful language acquisition occurs.' ([47] p. 22–23).

Another possibility is that SL and first language acquisition have a bidirectional link such that improvements in SL boost language, and vice versa. As mentioned earlier, most of the empirical evidence linking SL and language processing comes from assessments undertaken at a single point in time. Longitudinal research is needed for a variety of reasons: in order to shed light on whether SL improves, deteriorates or remains stable in children as these individuals get older, and in order to investigate whether any developmental trajectory that is observed is causally related to first language acquisition. Longitudinal research examining the link between SL and second language acquisition would also be valuable.

Importantly, if SL is a multi-component ability, particular SL tasks that draw more heavily on certain underlying components may be more likely to reveal a developmental trajectory. It also seems possible that different components may show different developmental trajectories (e.g. with some showing a peak in performance at an earlier age than others). Examining the components of SL within and across modalities may be especially worthwhile when considering the link between SL and first language acquisition and examining the nature of developmental trajectories.

In summary, for those interested in individual differences in language processing, the issue of age-related changes in SL is highly relevant. Of course, individual differences in language processing are a key focus in research on neurodevelopmental disorders such as autism. It is well known that some individuals with autism experience oral and also written language difficulties (e.g. [48–51]). Accordingly, there is growing interest in whether SL is affected in autism.

3. Autism and statistical learning

Of the studies that have been conducted to date, there have been mixed findings regarding the capacity for SL in those with autism. Some studies have reported impaired SL in individuals with autism; one study has reported enhanced SL in autistic adults. Other studies have reported no difference in SL when comparing those with and without autism. Findings have also been mixed with regard to the relationship between language and SL in autistic individuals. Some studies report a link, while others report no link. A close look at the previous research reveals some relatively straight forward methodological differences across the studies (e.g. regarding sample size and restricted sampling of high-functioning individuals). More interestingly, conceptualization of SL as a multi-component ability may assist in understanding some of these different findings.

One of the earliest studies in this area, by Brown and coworkers [52], compared a group of high-functioning children and adolescents with ASD ($n = 31$, 8–14 years of age) with typically developing peers ($n = 31$) across a range of behavioural tests of implicit learning, including artificial grammar learning, a contextual cueing task, a serial reaction time task and a probabilistic classification learning task (all tasks used visually presented stimuli). Their results showed intact and comparable implicit learning for individuals with ASD and typical peers. Of particular relevance here, analyses that moved beyond group-level comparisons in order to explore individual differences revealed no relationship between the degree of communication impairment (measured via the Social Communication Questionnaire; SCQ [53]) and performance on the implicit learning tasks. The focus on high-functioning individuals continued in subsequent studies of whether individual differences in language processing might be related to SL that were conducted by other researchers such as Mayo & Eigsti [54] and Scott-Van Zeeland *et al.* [55].

Similarly to the findings of Brown and co-workers [52], Mayo & Eigsti [54] reported intact SL in ASD and no difference between SL in individuals with and without ASD. In their study, Mayo & Eigsti assessed sequential SL of linguistic stimuli in the auditory modality using the embedded triplet paradigm (21 min for familiarization followed by a surprise 2AFC test phase) in high-functioning individuals with ASD ($n = 17$, 7–17 years) and typically developing peers ($n = 24$, 8–17 years). In addition to examining SL, a wide array of tests assessing cognition, ASD severity (as measured by the Autism Diagnostic Observation Schedule; ADOS [56]) and language were also administered. There was no relationship between SL and scores on tests assessing cognition or ASD. In line with Brown *et al.*, there was no relationship between SL and degree of language impairment (as measured by standardized tests of vocabulary, non-word repetition, sentence formation and comprehension in the Peabody Picture Vocabulary Test (PPVT-III [57]), Expressive Vocabulary Test (EVT [58]) and Clinical Evaluation of Language Fundamentals (CELF-4 [59])). However, despite their behavioural findings showing comparable SL in individuals with and without autism, Mayo & Eigsti [54] emphasized that there may well be neural processes associated with SL that differentiate individuals with ASD from typically developing peers.

If SL is a multi-component ability it seems possible that some components are better observed at the neural rather than the behavioural level. Regarding this point about possible differences between behavioural and imaging studies, it is interesting to note that an earlier fMRI study by Scott-Van Zeeland and co-workers compared a group of 18 high-functioning children and adolescents with ASD (9–16 years) with a group of 18 typically developing peers [55]. SL was assessed using the embedded triplet paradigm—familiarization streams of pseudospeech comprised of individually presented syllables were presented while children were in the scanner (three streams, which were each 144 s in duration). A test phase was administered outside of the scanner. Behavioural performance during the test phase was at chance, but group differences were discovered in terms of neural processing during familiarization. These group differences were interpreted as less sensitivity to statistical regularities in those with ASD. In addition, the study revealed a relationship between the degree of communication impairment (measured via the Autism Diagnostic Interview, Revised (ADI–R [60])) and neural processing during the SL task in those with ASD. Participants with less communication impairment showed greater signal increases during the SL task in left inferior parietal lobule (IPL) and putamen. Findings regarding group differences between those with and without ASD, and a link between communication impairment and SL in those with ASD, are contrary to the behavioural findings of Brown *et al.* [52] and Mayo & Eigsti [54].

Unlike previous studies that have focused primarily on high-functioning individuals with ASD, Jeste *et al.* [45] collected ERP data during a visual SL task with sequentially presented stimuli in a group of young children with ASD (2–6 years) and a group of age-matched typically developing peers. No behavioural data on SL were collected. Early negativity (N1) correlated with SL for all children in the study; however, there were some differences between electrophysiological responses in those with ASD versus typically developing children. These differences appeared to be driven by differences between low- and high-functioning children with ASD, suggesting that ASD is linked with variability in SL. In addition, in the ASD group there was a positive correlation between P300 amplitude collected during the SL task and adaptive behaviour (Vineland Adaptive Behavior Scales-II (VABS-II); [61]). As mentioned earlier, because the stimuli used by Jeste *et al.* [45] were coloured geometric shapes (e.g. pink diamond, yellow circle, blue cross), some individuals may have processed stimuli as particular shapes or colours. As such, explicit processes may have contributed to some of the effects reported in that study although it is difficult to speculate further, especially given lack of engagement by older participants.

Departing from a focus on sequential SL in many of the other studies in this area, Roser and co-workers examined the detection of spatial regularities in those with and without ASD [62]. If SL is comprised of multiple components, it is reasonable to expect that (at least some of) these components process spatial regularities differently from sequential regularities. Roser *et al.* examined children ($n = 28$ with ASD and $n = 22$ without ASD, both groups had a mean age of 13 years) and adults ($n = 10$ with ASD with a mean age of 41, and $n = 10$ without ASD with a mean age of 36.5). ASD groups included individuals with a previous diagnosis of high-functioning autism, Asperger's Syndrome, or ASD, however, all child participants were noted as being mainstream educated (i.e. very low-functioning children may not have been represented in the sample). The SL task was comprised of a familiarization phase followed by a surprise test phase (2AFC trials). During familiarization, stimuli were presented in different areas of a 3×3 grid (certain pairs of stimuli were presented in an invariant spatial relationship). Although the stimuli could loosely be described as shapes, they could not be easily verbalized and were presented as black figures against a white background (unlike the familiar coloured geometric shapes presented by Jeste *et al.* [45]).

The findings reported by Roser *et al.* [62] revealed intact SL in individuals with ASD—as well as a somewhat surprising finding of superior SL in adults with ASD by comparison with a control group of adults. Superior SL in individuals with ASD was not observed in the child data. The authors acknowledged their modest sample sizes and stated that their study 'does not allow for the full heterogeneity of the ASD spectrum to be represented' ([62], p. 169). They also noted that studies that rely solely on group-level comparisons, such as theirs, are not the most effective way to examine individual differences. As mentioned, if SL is comprised of multiple components we might expect that these components process spatial regularities differently from sequential regularities, although it is not clear why such components would be differentially affected by age in individuals in ASD compared with neurotypical peers.

With regard to further investigations of the link between SL and variability in language processing in ASD, several other issues are worthy of attention. It may be useful for future studies to incorporate language tasks that are specifically designed with embedded statistical regularities in mind and have previously revealed differences in performance between those with and without ASD (e.g. Arciuli & Paul [63]). Certainly, it is important for future investigations to include more representative samples of individuals with ASD rather than focusing only on those who are high-functioning. In addition, future research could explore whether (some of) the components underlying SL show a different developmental trajectory in individuals with and without ASD.

It would also be valuable for future research to move beyond assessment of immediate SL in order to explore retention/consolidation of SL. If SL contributes meaningfully to language acquisition, there must be retention/consolidation over time rather than just momentary computations. Moreover, if SL is a multi-component ability it may be that some components are more important for retention/consolidation than others. Exploring retention/consolidation of SL may shed light on the link between language acquisition and SL in individuals with ASD.

4. Retention and consolidation of statistical learning in autism

By way of brief background, there have been a handful of studies that have examined retention/consolidation of SL in neurotypical individuals. An early study of neurotypical adults (18–35 years) was reported by Kim *et al*. [64], who assessed sequential SL in the visual modality with an embedded triplet task. Stimuli were unfamiliar shapes presented as black figures against a white background. Participants were exposed to a familiarization phase followed 24 h later by a surprise test phase comprised of a rapid serial visual presentation (RSVP) task. Arciuli & Simpson [65] reported another study of neurotypical adults (17–25 years) using different visual stimuli (the aforementioned aliens in the embedded triplet task first reported in [44]). In a between-participants design, a familiarization phase was undertaken 30 min, 1 h, 2 h, 4 h or 24 h before a surprise test phase comprised of 2AFC trials. Significant SL was observed in each of these conditions. The results from both of these previous studies attest to the longevity of SL in neurotypical adults. For studies of retention/consolidation of SL and in infants, see [66,67] as well as the paper included in this special issue [68].

Might retention/consolidation of SL be disrupted in individuals with ASD? Certainly, it is well documented that many individuals with autism experience disturbed sleep (e.g. [69–73]). And there is growing interest in how retention and consolidation of learning that is associated with sleep might be related to language processing (e.g. [74,75]).

To date, only one study has investigated a possible link between SL and sleep in ASD [76]. In that study, Nemeth and co-workers used a visually presented four-element alternating serial reaction time task (ASRT) task to examine learning over 16 h (including a period of overnight sleep) in 14 children with ASD (7–17 years) and two control groups ($n = 14$ age-matched participants and $n = 13$ IQ-matched participants). Findings revealed intact and equivalent learning over time in groups with and without ASD. The authors of that study acknowledged that small sample size and ‘great variability in responses’ may have reduced statistical power to detect group differences [76, p. 5]. It is noteworthy that direct monitoring of sleep activity via polysomnography was not undertaken in the studies by Kim *et al*. [64], Arciuli & Simpson [65] or Nemeth *et al*. [76]. Such data are invaluable in determining whether SL might be related to individual differences in the type and/or duration of sleep.

Studies of neurotypical adults, and a study of adults with sleep apnoea, that have used direct monitoring of sleep activity via polysomnography have a found a link between SL and individual differences in non-rapid eye movement sleep (NREM) [77–79].[1] It has been suggested that NREM sleep may be important for SL through: (i) restoration of cellular homeostasis after the energy-rich processing of statistical regularities during waking periods, and (ii) consolidation and integration of learning via offline sampling of statistical regularities collected during waking periods [80]. See also [81] for discussion of sleep-dependent brain processes relating to SL.

Future studies could use polysomnography to determine whether there is a link between individual differences in NREM sleep, SL and language proficiency in ASD. It may be that only some of the components underpinning SL contribute to this link. The next section focuses more closely on the multiple components that may underpin SL and how research efforts might be directed at exploring this possibility.

5. Multiple components underpinning statistical learning

It is not entirely clear why the previous studies reviewed here have produced such divergent findings. While I have outlined methodological issues in each of the preceding sections, I have also put forward a more powerful explanation—the possibility that SL is a multi-component ability and that both individuals and SL tasks differ in terms of underlying components.

Components relating to the stimulus encoding, retention and abstraction required for SL may include, but are not limited to, certain types of attention, processing speed, and memory (both WM and longer-term memory). Viewing SL as a multi-component ability is compatible with the view that sensitivity to statistical regularities is domain-general but not necessarily uniform across modalities (e.g. [82–84]). It may well be that some of the components underpinning SL operate differently in different modalities. However, we can go a step further and speculate that even within modalities, some components of SL may operate differently depending on the stimuli and task instructions that are used. Investigation of how individuals vary in terms of the efficiency of underlying components, and connectivity among components, within and across modalities, may be helpful in explaining seemingly divergent findings relating to how SL interacts with age and also autism.

Interestingly, some of the components underpinning SL may interact with social cues (e.g. [85,86]). It has been suggested by Kuhl [87] that ‘Social cues ‘gate’ what and when children learn from language input.’ (p. 139). See also [88] for discussion on the interaction between SL and social cues. As such, an exciting line of research concerns the interaction between social cues and particular components of SL (e.g. attention). This may be an especially promising avenue of inquiry in autism research because of the link between difficulties with social cognition and autism; however, it is of relevance for understanding SL in any individual who is learning in the ‘real world’, outside of the laboratory and often in the company of others.

In terms of how SL tasks draw on some components more than others, previous studies have explored whether tests of SL might be measuring the same abilities assessed by commonly used tests of intelligence. For example, Evans *et al*. [22], Conway *et al*. [20] and Kidd & Arciuli [26] found that tasks of sequential SL were tapping into abilities that were independent of those assessed by tests of non-verbal intelligence. Kaufman *et al*. [24] found that variability in SL was independent of variability in general intelligence and WM but related to variability in processing speed. A study conducted by Siegelman & Frost [84] used an array of SL tasks assessing sequential learning and found that performance on these tasks was largely independent of performance on tests of non-verbal intelligence, WM and rapid naming. Only one of the five SL tasks included in that study was correlated with performance on only one of the cognitive measures, non-verbal intelligence.

Most of the studies mentioned above that have looked at the relationship between SL and other aspects of cognition have incorporated tests of cognition that measure explicit processing. In this sense, it is perhaps not surprising that performance on SL tasks, which are usually designed to assess implicit learning, is not highly correlated with performance on tasks that assess explicit processing. We will need to develop innovative ways to assess the components that comprise SL.

Exploration of implicit WM would be a good place to start. In one of the earliest empirical studies of individual differences in SL, Arciuli & Simpson [44] stated 'It seems likely that a task in which participants implicitly compute the statistical regularities that are present in sequentially delivered stimuli will recruit, among other processes, some kind of implicit mode of WM.' (p. 470). Later, Janacsek & Nemeth [89] made a similar observation: 'it seems plausible that a local short-term storage is necessary for processing sequence information (e.g. actively maintaining and binding several items in the sequence), although the exact nature of this short-term storage and its relation to WM [working memory] is still unexplored...even if such local short-term storage dedicated to SL exists, it seems unlikely to be connected to the classical concept of WM.' (p. 412).

Indeed, while it has generally been assumed that WM operates under conscious awareness, there is interest in developing tasks that assess WM which operates 'unintentionally and outside of conscious awareness' ([90], p. 675). See also [91], which reported on implicit WM and [92], which included discussion of WM in the context of implicit sequence learning. It is for future research to reimagine long-held beliefs about cognition, including aspects relating to attention, WM, longer-term memory, processing speed and so on, in order to develop new tests of implicit cognition and examine relationships between individuals' performance on these tests and accepted measures of SL.

Discovering the neural basis of the components that comprise SL will also assist our understanding of the nature of SL and how individual differences in SL are linked with development through infancy and early childhood in typically developing children and in those with neurodevelopmental disorders such as ASD. SL probably operates with the support of a variety of brain regions including networks within and across the hippocampus, the striatum and frontal regions (e.g. [79,93–98]). See also Yang & Li [99] for discussion of differences in implicit versus explicit learning networks in the brain. It has been pointed out that learning processes in these key brain regions may occur at different rates, thereby resulting in quite different types of behavioural effects depending on the learning task that is used [100]. Arciuli & Simpson [44] noted that some of the learning processes in different brain regions may be early-maturing while others are not. For example, see research on protracted neural development in fronto-parietal regions associated with WM [101]. We need to understand how individuals and SL tasks vary in terms of the components that comprise SL and how these components are subserved by different neural regions and processes.

6. Conclusion

The argument I have presented here is that SL is an ability comprised of multiple components that operate largely implicitly. Although empirical research is required to test this possibility, individuals probably vary in terms of the efficiency of these underlying components, and in patterns of connectivity among components. In addition, it seems highly likely that SL tasks differ from one another in the way they draw upon certain underlying components more than others. This theoretical framework can assist researchers interested in the link between SL and individual differences in complex mental activities such as language processing, especially those interested in typical child development and neurodevelopmental disorders like ASD where language can be affected. It may help in explaining divergent findings and in guiding the design of more illuminating future research.

Competing interests. I declare I have no competing interests.

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Endnote

[1]Note that unlike the study by Arciuli *et al.* [77], in the study by Durrant *et al.* [79] participants were made aware that there would be test phases after the familiarization phase. This may have implications regarding the proportion of explicit versus implicit knowledge in these different studies of SL. Note also that while the study by Arciuli *et al.* [77] used a completely different SL task, the studies by Durrant and co-workers [78,79] used a similar SL task (although the underlying sequential structure was simpler in [79]).

References

1. Franco A, Destrebecqz A. 2012 Chunking or not chunking? How do we find words in artificial language learning? *Adv. Cogn. Psychol.* **8**, 144–154. (doi:10.2478/v10053-008-0111-3)
2. Onnis L, Thiessen E. 2013 Language experience changes subsequent learning. *Cognition* **126**, 268–284. (doi:10.1016/j.cognition.2012.10.008)
3. Perruchet P, Desaulty S. 2008 A role for backward transitional probabilities in word segmentation? *Mem. Cognit.* **36**, 1299–1305. (doi:10.3758/MC.36.7.1299)
4. Perruchet P, Poulin-Charronnat B, Tillmann B, Peereman R. 2014 New evidence for chunk-based models in word segmentation. *Acta Psychol.* **149**, 1–8. (doi:10.1016/j.actpsy.2014.01.015)
5. Poletiek F, Wolters G. 2009 What is learned about fragments in artificial grammar learning? A transitional probabilities approach. *Q. J. Exp. Psychol. (Colchester)* **62**, 868–876. (doi:10.1080/17470210802511188)
6. Mareschal D, French RM. 2017 TRACX2: a connectionist autoencoder using graded chunks to model infant visual statistical learning. *Phil. Trans. R. Soc. B* **372**, 20160057. (doi:10.1098/rstb.2016.0057)
7. Thiessen ED. 2017 What's statistical about learning? Insights from modelling statistical learning as a set of memory processes. *Phil. Trans. R. Soc. B* **372**, 20160056. (doi:10.1098/rstb.2016.0056)
8. Perruchet P, Pacton S. 2006 Implicit learning and statistical learning: one phenomenon, two approaches. *Trends Cogn. Sci.* **10**, 233–238. (doi:10.1016/j.tics.2006.03.006)

9. Batterink LJ, Reber PJ, Neville HJ, Paller KA. 2015 Implicit and explicit contributions to statistical learning. *J. Memory Lang.* **83**, 62–78. (doi:10.1016/j.jml.2015.04.004)
10. Bertels J, Franco A, Destrebecqz A. 2012 How implicit is visual statistical learning? *J. Exp. Psychol. Learn. Memory Cogn*. **38**, 1425–1431. (doi:10.1037/a0027210)
11. Franco A, Cleeremans A, Destrebecqz A. 2016 Objective and subjective measures of cross-situational learning. *Acta Psychol.* **165**, 16–23. (doi:10.1016/j.actpsy.2016.02.001)
12. Arciuli J, von Koss Torkildsen J, Stevens D, Simpson I. 2014 Statistical learning under incidental versus intentional conditions. *Front. Psychol. Cogn. Sci.* **5**. (doi:10.3389/fpsyg.2014.00747)
13. Baker CI, Olson CR, Behrmann M. 2004 Role of attention and perceptual grouping in visual statistical learning. *Psychol. Sci.* **15**, 460–466. (doi:10.1111/j.0956-7976.2004.00702.x)
14. Bertels J, Destrebecqz A, Franco A. 2015 Interacting effects of instructions and presentation rate on visual statistical learning. *Front. Psychol.* **6**. (doi:10.3389/fpsyg.2015.01806)
15. Aslin R, Newport E. 2012 Statistical learning: from acquiring specific items to forming general rules. *Curr. Dir. Psychol. Sci.* **21**, 170–176. (doi:10.1177/0963721412436806)
16. Erickson L, Thiessen E. 2015 Statistical learning of language: theory, validity, and predictions of a statistical learning account of language acquisition. *Dev. Rev*. **37**, 66–108. (doi:10.1016/j.dr.2015.05.002)
17. Rohrmeier M, Rebuschat P. 2012 Implicit learning and acquisition of music. *Topics Cogn. Sci.* **4**, 525–553. (doi:10.1111/j.1756-8765.2012.01223.x)
18. Arciuli J, Von Koss Torkildsen J. 2012 Advancing our understanding of the link between statistical learning and language acquisition: the need for longitudinal data. *Front. Psychol. Lang. Sci.* **3**. (doi:10.3389/fpsyg.2012.00324)
19. Arciuli J, Simpson I. 2012 Statistical learning is related to reading ability in children and adults. *Cogn. Sci.* **36**, 286–304. (doi:10.1111/j.1551-6709.2011.01200.x)
20. Conway CM, Bauernschmidt A, Huang SS, Pisoni DB. 2010 Implicit statistical learning in language processing: word predictability is the key. *Cognition* **114**, 356–371. (doi:10.1016/j.cognition.2009.10.009)
21. Conway CM, Pisoni DB, Anaya EM, Karpicke J, Henning SC. 2011 Implicit sequence learning in deaf children with cochlear implants. *Dev. Sci.* **14**, 69–82. (doi:10.1111/j.1467-7687.2010.00960.x)
22. Evans JL, Saffran JR, Robe-Torres K. 2009 Statistical learning in children with specific language impairment. *J. Speech Lang. Hear Res.* **52**, 321–335. (doi:10.1044/1092-4388(2009/07-0189))
23. Frost R, Siegelman N, Narkiss A, Afek L. 2013 What predicts successful literacy acquisition in a second language? *Psychol. Sci*. **24**, 1243–1252. (doi:10.1177/0956797612472207)
24. Kaufman S, DeYoung C, Gray J, Jiménez L, Brown J, Mackintosh N. 2010 Implicit learning as an ability. *Cognition* **116**, 321–340. (doi:10.1016/j.cognition.2010.05.011)
25. Kidd E. 2012 Implicit statistical learning is directly associated with the acquisition of syntax. *Dev. Psychol.* **48**, 171–184. (doi:10.1037/a0025405)
26. Kidd E, Arciuli J. 2016 Individual differences in statistical learning predict children's comprehension of syntax. *Child Dev.* **87**, 184–193. (doi:10.1111/cdev.12461)
27. Misyak JB, Christiansen MH. 2012 Statistical learning and language: an individual differences study. *Lang. Learn.* **62**, 302–331. (doi:10.1111/j.1467-9922.2010.00626.x)
28. Spencer M, Kaschak MP, Jones JL, Lonigan CJ. 2015 Statistical learning is related to early literacy-related skills. *Reading Writing* **28**, 467–490. (doi:10.1007/s11145-014-9533-0)
29. Ellis EM, Gonzalez MR, Deák GO. 2014 Visual prediction in infancy: what is the association with later vocabulary? *Lang. Learn. Dev*. **10**, 36–50. (doi:10.1080/15475441.2013.799988)
30. Shafto CL, Conway CM, Field SL, Houston DM. 2012 Visual sequence learning in infancy: domain-general and domain-specific associations with language. *Infancy* **17**, 247–271. (doi:10.1111/j.1532-7078.2011.00085.x)
31. Alt M, Meyers C, Oglivie T, Nicholas K, Arizmendi G. 2014 Cross situational statistically based word learning intervention for late-talking toddlers. *J. Commun. Disord.* **52**, 207–220. (doi:10.1016/j.jcomdis.2014.07.002)
32. Onnis M, Lou-Magnuson M, Yun H, Thiessen E. 2015 Is statistical learning trainable? In *Proc. of the 37th Annual Meeting of the Cognitive Science Society* (eds DC Noelle, R Dale, AS Warlaumont, J Yoshimi, T Matlock, CD Jennings, Maglio PP), pp. 1781–1786. Austin, TX: Cognitive Science Society. See https://mindmodeling.org/cogsci2015/papers/0309/index.html.
33. Wells J, Christiansen M, Race D, Acheson D, MacDonald M. 2009 Experience and sentence processing: statistical learning and relative clause comprehension. *Cognit. Psychol.* **58**, 250–271. (doi:10.1016/j.cogpsych.2008.08.002)
34. Zuhurudeen FM, Huang YT. 2016 Effects of statistical learning on the acquisition of grammatical categories through Quranic memorization: a natural experiment. *Cognition* **148**, 79–84. (doi:10.1016/j.cognition.2015.12.014)
35. Reber AS. 1992 The cognitive unconscious: an evolutionary perspective. *Conscious Cogn.* **1**, 93–133. (doi:10.1016/1053-8100(92)90051-B)
36. Saffran JR, Newport EL, Aslin RN, Tunick RA, Barrueco S. 1997 Incidental language learning: listening (and learning) out of the corner of your ear. *Psychol. Sci.* **8**, 101–105. (doi:10.1111/j.1467-9280.1997.tb00690.x)
37. Kirkham NZ, Slemmer JA, Johnson SP. 2002 Visual statistical learning in infancy: evidence for a domain general learning mechanism. *Cognition* **83**, B35–B42. (doi:10.1016/S0010-0277(02)00004-5)
38. Thomas KM, Hunt RH, Vizueta N, Sommer T, Durston S, Yang Y, Worden MS. 2004 Evidence of developmental differences in implicit sequence learning: an fMRI study of children and adults. *J. Cogn. Neurosci.* **16**, 1339–1351. (doi:10.1162/0898929042304688)
39. Lewkowicz D. 2013 Development of ordinal sequence perception in infancy. *Dev. Sci.* **16**, 352–364. (doi:10.1111/desc.12029)
40. Marcovitch S, Lewkowicz D. 2009 Sequence learning in infancy: the independent contributions of conditional probability and pair frequency information. *Dev. Sci.* **12**, 1020–1025. (doi:10.1111/j.1467-7687.2009.00838.x)
41. Slone LK, Johnson SP. 2015 Infants' statistical learning: 2- and 5-month-olds' segmentation of continuous visual sequences. *J. Exp. Child Psychol.* **133**, 47–56. (doi:10.1016/j.jecp.2015.01.007)
42. Kirkham NZ, Slemmer JA, Richardson DC, Johnson SP. 2007 Location, location, location: development of spatiotemporal sequence learning in infancy. *Child Dev.* **78**, 1559–1571. (doi:10.1111/j.1467-8624.2007.01083.x)
43. Krogh L, Vlach H, Johnson SP. 2013 Statistical learning across development: flexible yet constrained. *Front. Psychol.* **3**. (doi:10.3389/fpsyg.2012.00598)
44. Arciuli J, Simpson I. 2011 Statistical learning in typically developing children: the role of age and speed of stimulus presentation. *Dev. Sci.* **14**, 464–473. (doi:10.1111/j.1467-7687.2009.00937.x)
45. Jeste SS *et al.* 2015 Electrophysiological evidence of heterogeneity in visual statistical learning in young children with ASD. *Dev. Sci*. **18**, 90–105. (doi:10.1111/desc.12188)
46. Locke J, Bogin B. 2006 Language and life history: a new perspective on the development and evolution of human language. *Behav. Brain Sci.* **29**, 259–325. (doi:10.1017/S0140525X0600906X)
47. Newport EL. 1990 Maturational constraints on language learning. *Cogn. Sci*. **14**, 11–28. (doi:10.1207/s15516709cog1401_2)
48. Kjelgaard M, Tager-Flusberg H. 2001 An investigation of language impairment in autism: implications for genetic subgroups. *Lang. Cogn. Process.* **16**, 287–308. (doi:10.1080/01690960042000058)
49. Loucas T, Charman T, Pickles A, Simonoff E, Chandler S, Meldrum D, Baird G. 2008 Autistic symptomatology and language ability in autism spectrum disorder and specific language impairment. *J. Child Psychol. Psych.* **49**, 1184–1192. (doi:10.1111/j.1469-7610.2008.01951.x)
50. Nash R, Arciuli J. 2016 Prosodic awareness is related to reading ability in children with autism spectrum disorders. *J. Res. Reading* **39**, 72–87. (doi:10.1111/1467-9817.12033)
51. Nation K, Clarke P, Wright B, Williams C. 2006 Patterns of reading ability in children with autism spectrum disorder. *J. Autism Dev. Disord.* **36**, 911–919. (doi:10.1007/s10803-006-0130-1)
52. Brown J, Aczel B, Jimenez L, Kaufman S, Grant K. 2010 Intact implicit learning in autism spectrum conditions. *Q. J. Exp. Psychol.* (*Colchester*) **63**, 1789–1812. (doi:10.1080/17470210903536910)

53. Rutter M, Bailey A, Lord C, Berument SK. 2003 SCQ: Social Communication Questionnaire. Los Angeles: Western Psychological Services.
54. Mayo J, Eigsti I. 2012 Brief report: a comparison of statistical learning in school-aged children with high functioning autism and typically developing peers. *J. Autism Dev. Disord.* **42**, 2476–2485. (doi:10.1007/s10803-012-1493-0)
55. Scott-Van Zeeland A, McNealy K, Wang A, Sigman M, Bookheimer S, Dapretto M. 2010 No neural evidence of statistical learning during exposure to artificial languages in children with autism spectrum disorders. *Biol. Psych.* **68**, 345–351. (doi:10.1016/j.biopsych.2010.01.011)
56. Lord C, Risi S, Lambrecht L, Cook EH, Leventhal BL, DiLavore PC, Pickles A, Rutter M. 2000 The autism diagnostic observation schedule-generic: a standard measure of social and communication deficits associated with the spectrum of autism. *J. Autism Dev. Disord.* **30**, 205–230.
57. Dunn LM, Dunn LM. 1997 *The peabody picture vocabulary test*, 3rd edn. Circle Pines, MN: American Guidance Service.
58. Semel E, Wiig EH, Secord WA. 2003 *Clinical evaluation of language fundamentals*, 4th edn. New York, NY: The Psychological Corporation.
59. Willimas KT. 1997 *Expressive vocabulary test*, Circle Pines, MN: American Guidance Service.
60. Lord C, Rutter M, LeCouteur A. 1994 Autism diagnostic interview-revised: a revised version of a diagnostic interview for caregivers of individuals with possible pervasive developmental disorders. *J. Autism Dev. Disord.* **23**, 659–685.
61. Sparrow SS, Cicchetti DV, Balla DA. 2005 *Vineland adaptive behavior scales*, 2nd edn.. Circle Pines, MN: AGS Publishing.
62. Roser M, Aslin R, McKenzie R, Zahra D, Fiser J. 2015 Enhanced visual statistical learning in adults with autism. *Neuropsychology* **29**, 163–172. (doi:10.1037/neu0000137)
63. Arciuli J, Paul R. 2012 Sensitivity to probabilistic orthographic cues to lexical stress in adolescent speakers with ASD and typical peers. *Q. J. Exp. Psychol.* (*Colchester*) **65**, 1288–1295. (doi:10.1080/17470218.2012.655700)
64. Kim R, Seitz A, Feenstra H, Shams L. 2009 Testing assumptions of statistical learning: is it long-term and implicit? *Neurosci. Lett*. **461**, 145–149. (doi:10.1016/j.neulet.2009.06.030)
65. Arciuli J, Simpson I. 2012 Statistical learning is lasting and consistent over time. *Neurosci. Lett*. **517**, 133–135. (doi:10.1016/j.neulet.2012.04.045)
66. Gomez R, Bootzin R, Nadel L. 2006 Naps promote abstraction in language-learning infants. *Psychol. Sci.* **17**, 670–674. (doi:10.1111/j.1467-9280.2006.01764.x)
67. Hupbach AR, Bootzin R, Nadel L. 2009 Nap-dependent learning in infants. *Dev. Sci.* **12**, 1007–1012. (doi:10.1111/j.1467-7687.2009.00837.x)
68. Gómez RL. 2017 Do infants retain the statistics of a statistical learning experience? Insights from a developmental cognitive neuroscience perspective. *Phil. Trans. R. Soc. B* **372**, 20160054. (doi:10.1098/rstb.2016.0054)
69. Allik H, Larsson J, Smedje H. 2006 Sleep patterns of school-age children with Asperger syndrome or high-functioning autism. *J. Autism Dev. Disord.* **36**, 585–595. (doi:10.1007/s10803-006-0099-9)
70. Armstrong K, Rowe M, Kohler W. 2015 Addressing sleep disturbances in children with autism spectrum disorders. *Ann. Pediatr. Child Health* **3**, 1054. See www.jscimedcentral.com/Pediatrics/pediatrics-3-1054.pdf.
71. Richdale A. 1999 Sleep problems in autism: prevalence, cause, and intervention. *Dev. Med. Child Neurol.* **41**, 60–66. (doi:10.1111/j.1469-8749.1999.tb00012.x)
72. Stores G, Wiggs L. 1998 Abnormal sleep patterns associated with autism: a brief review of research findings, assessment methods and treatment strategies. *Autism* **2**, 157–169. (doi:10.1177/1362361398022004)
73. Tudor M, Hoffman C, Sweeney D. 2012 Children with autism: sleep problems and symptom severity. *Focus Autism Other Dev. Disabil.* **27**, 254–262. (doi:10.1177/1088357612457989)
74. Gaskell G, Warker J, Lindsay S, Frost R, Guest J, Snowdon R, Stackhouse A. 2014 Sleep underpins the plasticity of language production. *Psychol. Sci.* **25**, 1457–1465. (doi:10.1177/0956797614535937)
75. Schreiner T, Rasch B. 2015 Boosting vocabulary learning by verbal cueing during sleep. *Cereb. Cortex* **25**, 4169–4179. (doi:10.1093/cercor/bhu139)
76. Nemeth D, Janaczek K, Balogh V, Londe Z, Mingesz R, Fazekas M, Jambori S. 2010 Learning in autism: implicitly superb. *PLoS ONE* **5**, e11731. (doi:10.1371/journal.pone.0011731)
77. Arciuli J, Vakulin A, D'Rozario A, Openshaw H, Stevens D, McEvoy D, Wong K, Rae C, Grunstein R. 2015 Is statistical learning affected by sleep apnea? In *Proc. of the EuroAsianPacific Joint Conference on Cognitive Science* (eds G Airenti, B Bara, G Sandini), pp. 494–498. Turin, Italy. See http://ceur-ws.org/Vol-1419/paper0080.pdf.
78. Durrant S, Taylor C, Cairney S, Lewis P. 2011 Sleep-dependent consolidation of statistical learning. *Neuropsychologia* **49**, 1322–1331. (doi:10.1016/j.neuropsychologia.2011.02.015)
79. Durrant S, Cairney S, Lewis P. 2013 Overnight consolidation aids the transfer of statistical knowledge from the medial temporal lobe to the striatum. *Cereb. Cortex* **23**, 2467–2478. (doi:10.1093/cercor/bhs244)
80. Tononi G, Cirelli C. 2014 Sleep and price of plasticity: from synaptic and cellular homeostasis to memory consolidation and integration. *Neuron* **81**, 12–34. (doi:10.1016/j.neuron.2013.12.025)
81. Urbain C, Schmitz R, Schmidt C, Cleeremans A, Van Bogaert P, Maquet P, Peigneux P. 2013 Sleep-dependent neurophysiological processes in implicit sequence learning. *J. Cogn. Neurosci.* **25**, 2003–2014. (doi:10.1162/jocn_a_00439)
82. Conway CM, Christiansen MH. 2005 Modality-constrained statistical learning of tactile, visual, and auditory sequences. *J. Exp. Psychol. Learn. Mem. Cogn.* **31**, 24–39. (doi:10.1037/0278-7393.31.1.24)
83. Frost R, Armstrong BC, Siegelman N, Christiansen MH. 2015 Domain generality versus modality specificity: the paradox of statistical learning. *Trends Cogn. Sci.* **19**, 117–125. (doi:10.1016/j.tics.2014.12.010)
84. Siegelman N, Frost R. 2015 Statistical learning as an individual ability: theoretical perspectives and empirical evidence. *J. Memory Lang.* **81**, 105–120. (doi:10.1016/j.jml.2015.02.001)
85. Wu R, Kirkham N. 2010 No two cues are alike: depth of learning during infancy is dependent on what orients attention. *J. Exp. Child Psychol.* **107**, 118–136. (doi:10.1016/j.jecp.2010.04.014)
86. Wu R, Gopnik A, Richardson D, Kirkham N. 2011 Infants learn about objects from statistics and people. *Dev. Psychol.* **47**, 1220–1229. (doi:10.1037/a0024023)
87. Kuhl P. 2011 Early language learning and literacy: neuroscience implications for education. *Mind Brain Educ.* **5**, 128–142. (doi:10.1111/j.1751-228X.2011.01121.x)
88. Meltzoff AN, Kuhl P, Movellan J, Sejnowski T. 2009 Foundations for a new science of learning. *Science* **17**, 284–288. (doi:10.1126/science.1175626)
89. Janacsek K, Nemeth D. 2015 The puzzle is complicated: when should working memory be related to implicit sequence learning, and when should it not? (Response to Martini *et al*.). *Cortex* **64**, 411–412. (doi:10.1016/j.cortex.2014.07.020)
90. Hassin RA, Bargh JA, Engell AD, McCulloch KC. 2009 Implicit working memory. *Conscious Cogn.* **18**, 665–678. (doi:10.1016/j.concog.2009.04.003)
91. Soto D, Mäntylä T, Silvanto J. 2011 Working memory without consciousness. *Curr. Biol.* **21**, R912–R913. (doi:10.1016/j.cub.2011.09.049)
92. Janacsek K, Nemeth D. 2013 Implicit sequence learning and working memory: correlated or complicated? *Cortex* **49**, 2001–2006. (doi:10.1016/j.cortex.2013.02.012)
93. Janacsek K, Ambrus G, Paulus W, Antal A, Nemeth D. 2015 Right hemisphere advantage in statistical learning: evidence from a probabilistic sequence learning task. *Brain Stimulation* **8**, 277–282. (doi:10.1016/j.brs.2014.11.008)
94. Karuza EA, Newport EL, Aslin RN, Starling SJ, Tivarus ME, Bavelier D. 2013 The neural correlates of statistical learning in a word segmentation task: an fMRI study. *Brain Lang.* **127**, 46–54. (doi:10.1016/j.bandl.2012.11.007)
95. Schapiro AC, Kustner LV, Turk-Browne NB. 2012 Shaping of object representations in the human medial temporal lobe based on temporal regularities. *Curr. Biol.* **22**, 1622–1627. (doi:10.1016/j.cub.2012.06.056)
96. Schapiro AC, Gregory E, Landau B, McCloskey M, Turk-Browne NB. 2014 The necessity of the medial temporal lobe for statistical learning. *J. Cogn. Neurosci.* **26**, 1736–1747. (doi:10.1162/jocn_a_00578)

97. Turk-Browne NB, Scholl BJ, Chun MM, Johnson MK. 2009 Neural evidence of statistical learning: efficient detection of visual regularities without awareness. *J. Cogn. Neurosci.* **21**, 1934 – 1945. (doi:10.1162/jocn.2009.21131)

98. Turk-Browne NB, Scholl B, Johnson MK, Chun MM. 2010 Implicit perceptual anticipation triggered by statistical learning. *J. Neurosci.* **30**, 11 177 – 11 187. (doi:10.1523/JNEUROSCI.0858-10.2010)

99. Yang J, Li P. 2012 Brain networks of explicit and implicit learning. *PLoS ONE* **7**, e42993. (doi:10.1371/journal.pone.0042993)

100. Bays B, Turk-Browne N, Seitz A. 2016 Dissociable behavioural outcomes of visual statistical learning. *Visual Cogn.* **23**, 1072 – 1097. (doi:10.1080/13506285.2016.1139647)

101. Kwon H, Reiss A, Menon V. 2002 Neural basis of protracted developmental changes in visuo-spatial working memory. *Proc. Natl Acad. Sci. USA* **99**, 13 336 – 13 341. (doi:10.1073/pnas.162486399)