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Sleep promotes phonological learning in children across language and autism spectra

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Abstract

Purpose: Establishing stable and flexible phonological representations is a key component of language development, and one which is thought to vary across children with neurodevelopmental disorders affecting language acquisition. Sleep is understood to support the learning and generalisation of new phonological mappings in adults; but this remains to be examined in children. This study therefore explored the time-course of phonological learning in childhood and how it varies by structural language and autism symptomatology.

Method: Seventy-seven 7-13 year old children, 30 with high autism symptomatology were included in the study; structural language ability varied across the sample. Children learned new phonological mappings based on synthesised speech tokens in the morning; performance was then charted via repetition (without feedback) over 24 hours, and followed up four weeks later. On the night following learning, children's sleep was monitored with polysomnography.

Results: A period of sleep but not wake was associated with improvement on the phonological learning task in childhood. Sleep was associated with improved performance for both trained items and novel items. Structural language ability predicted overall task performance, though language ability did not predict degree of change from one session to the next. By contrast, autism symptomatology did not explain task performance. With respect to sleep architecture, REM features were associated with greater phonological generalisation.

Conclusion: Children's sleep was associated with improvement in performance on both trained and novel items. Phonological generalisation was associated with brain activity during REM sleep. This study furthers our understanding of individual differences in the acquisition of new phonological mappings and the role of sleep in this process over childhood.

Key words: phonological learning; phonological generalisation; sleep; children; REM; NREM

1.0 Introduction

1.1 The establishment and use of phonological representations

Phonological representations are units of knowledge in long-term memory describing the sounds that make up words (Stackhouse & Wells, 1997). The representation of speech sounds is perhaps the most fundamental element of language perception and production, forming the basis of phonological and orthographic word form as well as being critical to the processing of morpho-syntactic structure (Joanisse & Seidenberg, 2002). Speech sounds are understood to be represented categorically, with greater perceptual distance between points of equivalent acoustic distance when those points cross a category boundary compared to when they fall within a category (Chang et al., 2010; Liberman, Harris, Hoffman & Griffith, 1957). The establishment and use of phonological representations demands a fine balance. Phonological categories must be sufficiently well-defined to support speech perception by allowing the recognition of distinct phonemes; yet the system must also be flexible enough to allow an adaptive response to the changing linguistic environment, allowing new phoneme categories to be formed and established categories to be adjusted when listeners face inter- and intra-speaker variation (see Earle & Myers, 2014). When listening to someone with an unfamiliar accent, for example, a listener 'tunes in' over time, expanding and adapting the category requirements for different phonological categories and generalising learned adaptations to new contexts as they are heard (e.g., Whitteman, Bardhan, Weber & McQueen, 2015).

Children are thought to vary in the specificity with which speech sounds are represented. Although not ubiquitously (Coady, Kluender & Evans, 2005), many studies have found that children with developmental disorders of oral language perception and production have noisy, or poorly specified phonological representations. For example, children with developmental language disorder (DLD) show weak discrimination of speech sounds across boundary points (Robertson, Joanisse, Desroches & Ng, 2009; Stark & Heinz, 1996; Vanderwalle, Boets, Ghesquie & Zink, 2012), struggle to perceive speech in noise (Knowland et al., 2016; Vanderwalle et al., 2012; Ziegler et al., 2005, 2011), and exhibit poor lexical decision making when non-words are phonologically similar to existing words (Maillart, Schelstraete & Hupet, 2004). Poorly specified, noisy phonological representations have been proposed to underlie morphological difficulties, which are a hallmark of DLD (Joanisse, 2004; Joanisse & Seidenberg, 2002). The precision of phonological representations also varies between typically developing children within an age group (Anthony et al., 2010), and across developmental time (Hazan & Barett, 2000). We might expect that specificity with which speech sounds are represented is therefore associated with structural language ability.

Individuals with autism spectrum disorders (ASD) do not tend to show atypicalities in the perceptual categorisation of speech sounds (Constantino et al., 2007; Stewart, Petrou & Ota, 2018; although see Wang et al., 2017 for a study on the categorisation of lexical tone). However, there is some evidence for reduced phonetic generalisation in this population (Järvinen-Pasley et al., 2008); that is, a reduced ability to apply learning about speech sounds from one situation to another. Compared to controls, individuals with ASD demonstrate less generalisation across speech sounds when trained to imitate words with a modified phonetic feature (increased VOT) (Mielke, Nielsen & Magloughlin, 2013). The ability to generalise is critical to the flexibility of the phonological system. Generalisation allows the listener to adapt to inter-speaker variation, such as a previously un-encountered accent, or intra-speaker variation, such as phonetic variability as speakers encounter different acoustic backgrounds (see Kleinschmidt & Jaeger, 2015). Generalisation also allows listeners to transfer that learning to new words from the accented speaker or new speakers in the same noisy conditions.

In this study we assessed the time-course of phonological learning in a task that evaluated performance on both trained items, and novel items, assumed to rely more heavily on generalisation. Our aim was to probe the nature of the phonological system in children who were thought to vary in the stability and flexibility of their phonological representations, that is, in children who vary in structural language ability and autism symptomatology. Notably, many children with an ASD also show broad weaknesses in structural language ability (see Williams, Botting & Boucher, 2008 for a review) and many children with poor structural language show symptoms of ASD. By sampling across spectra of ability here we were able to assess the implications of poor structural language and autism symptomatology in the same children.

1.2 Phonological learning is supported by sleep

Perceptual learning related to speech sounds can be rapid, but the establishment of stable representations takes time and, as some evidence suggests, sleep. In typically developing young adults, Fenn and colleagues (Fenn, Nusbaum & Margoliash, 2003; Fenn, Margoliash, Nusbaum, 2013) have demonstrated that sleep promotes the generalisation of perceptual learning when listening to synthesised 'text-to-speech' tokens. Fenn et al (2013) tested adults on their ability to understand single synthesised words at four time points: before and after a perceptual training session at 9am, then 12 and 24 hours later. Two groups of participants were included. The generalization-trained group were trained by listening to

300 different synthetic words while being presented simultaneously with the written words. After 30 minutes of training, participants showed around a 20% improvement in their ability to type out previously unheard synthesised words; this training effect had decayed 12 waking hours later but was restored to post-training levels after sleep. A separate rote-trained group were trained on a limited set of 20 items, each repeated 15 times over the course of training. This group showed improvement when tested on the same items they were exposed to during training, but not when tested on novel items, even after sleep. Fenn and colleagues suggest that sleep therefore supports the generalisation of phonological re-mapping in adults. The importance of sleep for generalisation is supported by previous work from this same group showing that phonological generalisation after training on synthesised speech is restored to post-training levels after sleep in adults trained in the evening, but not after an equivalent period of wake in adults trained in the morning (Fenn et al., 2003).

Other work on the time-course of phonological generalisation has considered adult listeners' ability to generalise between foreign accented speakers after, for example, adapting to initially ambiguous speech sounds during lexically-guided learning. After perceptual adaptation to one accented speaker, immediate generalisation to others has been demonstrated when acoustic properties relevant to perceptual contrasts of interest are similar between speakers (Xie & Myers, 2016). When speakers differ phonetically, however, listeners' ability to generalise perceptual learning across speakers was observed only after a period of sleep, and not an equivalent wake period (Earle & Myers, 2015; Xie, Earle & Myers, 2018). This suggests that sleep supports the abstraction of higher-level category-relevant information from speech. Not all studies of phonological learning have shown a privileged role for sleep, however; for example, perceptual adjustments such as adapting to altered voice-onset times (Collet et al., 2012) or place of articulation (Eisner &

McQueen, 2006) for a single phonological contrast are not usually shown to be sleep-dependent in adults. This suggests that relatively straightforward modifications to the phonological system or to individual phonemic features are stable enough to not require over-night consolidation (see Earle & Meyers, 2014). The exact conditions under which sleep may support phonetic learning is not clear though, as even the identification and discrimination of a single non-native contrast has been shown to be sleep dependent (Earle, Landi & Myers, 2017).

Recently, Earle, Landi & Myers (2018) trained and immediately tested adults with and without DLD on non-native speech sounds in the evening then re-tested performance the following morning. Adults with DLD showed comparable gains to age-matched controls during training, but did not show overnight consolidation on the identification and discrimination of the newly learned sounds. The literature therefore suggests that sleep promotes complex phonological learning in typically developing adults, but may not provide the same degree of support for individuals who show relatively poor structural language skill.

The mechanisms by which sleep supports human memory in general are beginning to come into focus. Sleep can be broadly divided into Rapid Eye Movement (REM) sleep, and Non-REM sleep (consisting of Stage 1, Stage 2 and Slow-wave Sleep; SWS). Over the course of a night humans cycle through these stages, alternating between Non-REM and REM sleep around four or five times. One influential two-phase model of the role of sleep in memory consolidation (Diekelmann & Born, 2010) proposes that each stage of sleep actively contributes to different components of consolidation in a complementary manner, with the cyclical nature of sleep stages illustrating the inter-play between those components.

Diekelmann and Born suggest that Non-REM sleep supports *system consolidation*, whereby memory traces, encoded during the preceding period of wakefulness, are re-activated through co-ordinated activity between the hippocampus and neocortex. The re-activation of memory traces is thought to drive the relocation of trace-specific activity from short-term hippocampal to long-term neocortical storage. The mechanisms of mnemonic redistribution during system consolidation have been further supported and refined through evidence of hierarchical, nested activity during SWS (Staresina et al., 2015). Specifically, neocortically-generated slow oscillations during SWS, thalamocortically-generated spindles (bursts of activity at around 10-16Hz), and hippocampally-generated ripples (bursts of activity at around 80-100 Hz) are functionally coupled in the human hippocampus. This process is believed to be orchestrated by slow oscillations, with behavioural change in hippocampally dependent memory being associated with the coupling of oscillatory activity (Cox et al., 2012; Latchourmane, Ngo, Born & Shin, 2017). Wei et al. (2018) further propose that spindles in Stage 2 sleep promote the reactivation and consolidation of multiple competing memory traces, while SWS preferentially consolidates stronger traces.

The second component of Diekelmann and Born's two-phase model proposes that the period of REM sleep following Non-REM sleep promotes so called *synaptic consolidation* in localised neocortical regions, allowing the stabilisation of memory traces in long-term storage and enhancing the automaticity of signal processing. Sequential stages of sleep are therefore thought to act in concert to promote the reorganisation and consolidation of memory, with the action of stages depending on the type of memory, the task used and the strength of the memory trace at encoding.

Earle and Myers (2014) have suggested that the characteristics of sleep architecture (patterns of overnight brain activity) that phonological learning is associated with should vary depending on the task at hand. Tasks that rely more on auditory skill might be expected to be more strongly associated with REM-related synaptic consolidation, promoting a shift of attention to selective auditory features resulting in enhanced perceptual performance. By contrast, tasks that involve a greater degree of explicit recall or the integration of new memory traces with existing knowledge are likely to be associated to a greater extent with NREM-related system consolidation.

1.3 The current study

In this study we trained children, who varied in their structural language ability and autism symptomatology, to listen to synthesised speech tokens. We tracked changes in performance immediately after training (in the morning) then around 12 and 24 hours after training. At each test point children were asked to identify words on which they had been trained (Trained condition) as well as to generalise their learning to un-trained words (Novel condition). Our behavioural task was based on the paradigm developed by Fenn et al. (2013) with the crucial difference that while these authors used a between-participants design with separate generalised and rote learning regimes, here we used a single learning regime in a within-participants design. This change was made to and to ease the recruitment of difficult-to-reach populations. While this approach allowed us to compare performance on trained and novel items in the same participants, it prevented an analysis of the links between sleep and rote learning per se, as participants could bring to bear their broader experience during training when listening to both trained and novel items. To assess the role of sleep in the time-course of phonological learning, children were asked to wear polysomnography (PSG) sensors for the night after learning. Analysis of these data charts the time-course of phonological learning and generalisation, as well as relationships between sleep characteristics and phonological learning.

The current task required children to develop new phonological mappings by including synthetic tokens as acceptable exemplars of existing phonological categories, and to apply that learning to trained and novel contexts. As this involves complex re-mapping of phonological representations, we expected to see an improvement in performance overnight (based on previous adult data from Earle & Myers, 2014; and Fenn et al., 2003; 2013), but not over the wake interval. We further made two hypotheses regarding the relationship between behavioural change and aspects of sleep architecture. Firstly, we hypothesised that phonological learning would be associated with synaptic consolidation during REM sleep, as indexed by theta power. This hypothesis is based on the prediction by Earle and Myers (2014) that tasks requiring a shift of attention towards relevant acoustic features of phonological stimuli to enhance perceptual performance will be most strongly associated with REM sleep. This is supported both by research showing that phonological learning is associated with attentional shifts to relevant acoustic cues and that perceptual learning is linked to REM sleep. The task at hand here, for both trained and novel conditions, requires participants to attend to linguistically informative acoustic cues in the synthesised speech. Exactly this kind of selective attentional shift to acoustic cues has been demonstrated in adults to support the categorisation of ambiguous synthesised diphones, as well as generalisation to novel contexts (Francis, Baldwin & Nusbaum, 2000). A specific role for REM sleep is suggested by the finding that REM stabilises performance on a visual perceptual learning task (Tamake, Watanabe & Sasaki, 2017). We hypothesised that generalisation would be additionally related to system consolidation, as indexed by spindle activity and power during NREM sleep, as it relies on the integration of new information with existing phonological knowledge. Indeed, the generalisation of grammatical rules has been experimentally boosted by re-exposing participants to an artificial grammar during slow wave sleep (Batterink & Paller, 2017); and over a nap, the extraction of linguistic rules has been linked to co-ordinated activity across slow wave and REM sleep (Batterink, Oudiette, Reber & Paller, 2014). In addition, Earle and colleagues (Earle et el., 2017) found an association between performance on the identification of a newly learned non-native phoneme and NREM sleep (Stages 1 & 2), possibly because this task required the integration of a new contrast into an existing phonological category. Here we could expect to see a relationship between NREM sleep parameters and overnight change in performance on either condition, given that participants will be able to use their broader experience during training to support perception in both Novel and Trained tasks. We might expect stronger associations between REM sleep and performance on trained items, and between NREM sleep and performance on novel items. We therefore consider brain activity during both REM and NREM (Stage 2 and SWS) sleep in relation to both conditions here.

Although there is less work considering the role of sleep in phonological learning across childhood, existing evidence supports our hypothesis that sleep should play a role in the establishment of new phonological knowledge. Recognition and recall of newly learned word forms, as well as the integration of word forms with existing lexical representations, improves 24 hours after learning in 7-10 year old children (Henderson, Devine, Weighall & Gaskell, 2015). Similar improvements are only seen over a 12 hour interval for 7-12 year olds when that interval includes sleep (Henderson, Weighall, Brown & Gaskell, 2012). It is possible that the benefits of sleep for novel word learning seen over the primary school years are linked to the particular dominance of slow wave sleep in childhood, with slow wave sleep both accounting for a greater proportion of total sleep time in childhood (Ohayon, Carskadon, Guilleminault & Vitiello, 2004) and being of greater amplitude compared to adults (AASM, 2016).

We hypothesised that children with high autism symptomatology (above diagnostic threshold on a parent report screener) would show less phonological generalisation than their peers with low autism symptomatology (Järvinen-Pasley et al., 2008; Mielke et al., 2013), and that sleep variables would be associated with these difficulties in phonological generalisation. This association was expected given that children with a profile of ASD have frequently been reported to show atypical behavioural patterns of sleep as well as different sleep architecture compared to typically developing peers. In a meta-analysis of objective sleep measures (including PSG and actigraphy) in children with ASD, Elrod and Hood (2015) report 'small but measurable' differences compared to typically developing peers, including a longer sleep onset time (the time it takes to get to sleep once the lights are off) and shorter overall sleep time, with problems shown to be exacerbated in lower functioning children. With respect to the architecture of sleep, few studies exist, but those that do (see Díaz-Román et al., 2018 for a meta-analysis) point most consistently to a decrease in the density of spindles in Stage 2 sleep compared with typically developing peers (Godbout et al., 2000; Limoges et al., 2005; Tessier et al., 2015). One study did not find a difference in spindle density (Maski et al., 2015), though the team did report reduced time in REM sleep, a finding which has been mirrored elsewhere (Limoges et al., 2005). The literature on sleep in ASD points to the hypothesis that reduced sleep, and a reduced number of spindles in sleep may contribute to atypical phonological generalisation the day after training. Children in our sample also varied with respect to structural language ability, which we hypothesised would predict the extent and rate of phonological learning for both Trained and Novel conditions. No hypotheses were made about how language variability might relate to sleep, as while some preliminary evidence exists of sleep difficulties in children with language disorders based on parent report (Botting & Baraka, 2017; Dominick et al., 2007), the relationship remains largely un-explored.

2.0 Method

2.1 Participants

Participants were recruited to this study as part of the SleepSmart project at the University of York. For this phase of the project 79 participants were recruited, two of whom did not provide behavioural data relevant to this study and were therefore not included the analysis. Seventy-seven children (47 males), with an average age of 10 years and 1 month completed the study (SD = 17 months, range: 7 years 1 month – 12 years 9 months). Children were excluded from participation if they had been regularly exposed to a language other than English from birth, had a history of epileptic seizures, had a genetic syndrome, or if they did not have sufficient oral language to give informed oral assent to take part. Four children were reported to be taking melatonin to support sleep at the time of the study, three of whom had a diagnosis of ASD and one who was undergoing assessment for ASD; children were not asked to refrain from taking their usual medication to participate.

2.1.1. Measuring autism and language ability

Children were recruited to provide substantial variability in language ability in those with low and high autism symptomatology. Participants were divided into two groups based on autism symptomatology as measured by the Gilliam Autism Rating Scale, 3rd Edition (GARS3, Gilliam, 2013). The GARS3 is a parent report screening measure which was norm-referenced with an autistic cohort. It provides an *Autism Index* score indicating whether a diagnosis of autism is 'unlikely', 'probable' or 'very likely' for a given child or young adult. The Autism Index score is a composite which reflects subscales covering restrictive and repetitive behaviours, social interaction and cognitive and emotional processing. In the current study, the Low Autism Index (Low AI) group consisted of 47 children (mean age = 9 years and 10 months, SD = 17.0 months; 24 male and 23 female). Six children in the Low AI group scored below the 10th percentile on two or more standardised language tasks (see Table 1), consistent with a profile of developmental language disorder (DLD), one further child scored below the 10th percentile on the Elision subscale of the CTOPP2. Five children in the Low AI group had a sibling with a diagnosis of ASD, and three of these children scored in the 'probable' range on the GARS-3 (mean Autism Index = 56.8, SD = 8.1). A further three children, who were otherwise believed to be typically developing scored within the 'probable' range. The remaining 32 children in the Low AI group performed within the normal range on all cognitive measures, and within the 'unlikely' range on the GARS-3.

The High AI group consisted of 30 children (mean age = 10 years and 6 months, SD = 16.6 months), 23 of whom were male and 7 female. All of the children in this group scored within the 'very likely' range on the GARS3 (mean Autism Index = 99, SD = 13.5). Within the High AI group, 14 children had a diagnosis on the autism spectrum from a paediatrician, clinical psychologist or a multi-disciplinary team; a further 11 were undergoing diagnosis at the time of testing. Although not all children in our sample had a diagnosis at the time of testing, on average it takes 3 ½ years to get a diagnosis in the UK (Crane et al., 2015) and four of the children awaiting diagnosis at the time of testing are known to have received their diagnosis by the time this paper was submitted for publication. Of these 25 children, five had a language profile consistent with DLD even though they did not have additional diagnoses. In addition to the 25 children who had confirmed or pending diagnoses of ASD, a further five were included in a 'High AI' group as they scored in the 'very likely' range on the GARS3; four of these children had a diagnosis of a developmental disorder of language.

Although some children met clinical criteria for DLD, in this study we treat language as a continuous variable. We did not adopt this approach with the GARS3 as this measure resulted in two distinct groups (i.e., at either end of the spectrum of GARS3 scores), which were not described by a normal distribution; in addition, the GARS3 is a parental report measure, which may be biased by pre-existing parental views, potentially reflecting the stage families are at in the diagnostic process. The distribution of GARS3 scores reflected our recruitment efforts. By contrast, our language measures were objective, standardised tests. Children's Communication Checklist, 2nd Edition (CCC-2; Bishop, 2003) profiles suggest that the sample as a whole spanned a wide range of ability along both structural and social language continua (see Figure 1 for the distribution of scores on the GARS-3 and CCC-2 along with cognitive profiles by group in Table 1).

Table 1 and Figure 1 about here

2.2 Materials

Auditory stimuli were generated using a Votrax SC-01-A text-to-speech synthesiser[1]

[1] Can be found at http://real-votrax.no-ip.org/

(Gagnon, 1978). We used synthesised speech firstly to align our paradigm with Fenn and colleagues (2003, 2013), and secondly because the degradation seen in synthesised speech is non-uniform across cues, such that listeners cannot make simple perceptual adjustments in order to map degraded speech to established phonology. The Votrax synthesiser is a formant-based synthesis-by-rule program, whereby formant synthesised speech is built on the fly, based on rules regarding the acoustic properties of formant transitions. Synthesised words are built using a directory of 64 phonemes, concatenated using rules to model co-articulation and inflection. The overall impression is of a male robot with a slight American accent. Tokens were individually synthesised and downloaded in wav format with a sampling rate of 44.1 kHz.

The stimulus set was composed of nine lists of 25 concrete nouns: 225 words in total (see Appendix A). Over the course of the experiment, all participants were exposed to all lists: one at pre-test, four plus the pre-test list in training and four in post-tests (one plus the pre-test list in each post-test). The word lists were balanced with respect to: syllable and phoneme number, frequency of occurrence in spoken US English (Brysbaert & New, 2009), age of acquisition (Kuperman et al., 2012), phonotactic probability (segment average and biphone average; Vitevitch & Luce, 2004), concreteness (Brysbaert et al., 2014) and the percentage of the words that were made up of the 10 most common phonemes in spoken American English (Mines, Hanson & Shoup, 1978); see Table 2 for details of these variables across lists. A pilot study with adults was run in order to make sure that naive listeners would not perform at floor on the task. Words between one and four syllables in length were selected for inclusion in the lists if between 20 and 90% of adult listeners correctly identified them on first hearing, if they were highly concrete, and if they had an age-of-acquisition of less than seven years. A few items had an age-of-acquisition over seven years, including ‘dustbin’, ‘badger’ and ‘hedgehog’, but these items were included as the Kuperman ratings are from an American sample and British children were judged to learn these words at a younger age than their American counterparts. Each token was normalised and any DC offset was removed using Audacity (The Audacity Team, 1999-2017). Stimuli were always presented on a laptop with over-ear Superlux headphones at a comfortable listening volume.

Table 2 about here

2.3 Design and procedure

Participants were seen at five time points: once for an initial assessment of cognitive ability, three times over the course of 24 hours (Day1:AM in the morning of the first day, Day1:PM in the evening around 12 hours later, and Day2:AM on the morning of the second day), then once again at follow-up around four weeks later (Follow-Up). The dependent variable in this study was proportion of words correctly repeated (accuracy). Independent variables were Group (High AI, Low AI), Language composite score and sleep architecture between participants, and Condition (Trained, Novel) and Session (Day1:AM-pre, Day1:AM-post, Day1:PM, Day2:AM, Follow-Up) within participants.

Each participant was designated one Trained list, which they heard at pre-test, during training and at each subsequent post-test after training. Four additional lists were used during training, then at each post-test participants heard one Novel list along with their Trained list. Pseudo-random counterbalancing was achieved by establishing nine different permutations of list exposure and assigning participants to one of these permutations sequentially as testing progressed. Testing was completed in a one-to-one setting with one of a small team of researchers, and was conducted either at the child's home, school or in the Department of Psychology at the University of York. All children who completed behavioural testing for this study were also participants in a study of semantic learning, training and testing for which were completed during the Day1:PM and Day2:AM sessions (see Fletcher et al., submitted).

2.3.1 Cognitive assessments

The following standardised assessments were administered in accordance with published guidelines, always in the same order: British Picture Vocabulary Scale, 3rd Edition (BPVS-3; Dunn, Dunn & Styles, 2009); The Matrices, Forward Digit Recall, Word Definitions, and Backward Digit Recall subscales from the British Ability Scales, 3rd Edition (BAS3; Elliott & Smith, 2011); Recalling Sentences subscale from the Clinical Evaluation of Language Fundamentals 4th Edition (CELF-4; Semel & Wiig, 2006); Elision, Rapid Automatic Naming (RAN- Digits and Letters) and Non-Word Repetition from the Comprehensive Test of Phonological Processing, 2nd Edition (CTOPP2; Wagner, Torgesen, Rashotte & Pearson, 2013), NWR was re-recorded by a female speaker of British English with a southern accent, trained in phonetics. The parents of all children were also asked to complete a series of questionnaires about their child: The Children's Sleep Habits Questionnaire (CSHQ, Owens, Spirito & McGuinn, 2000); The Child Behaviour Checklist (CBCL, Achenbach & Edelbrock, 1983), The Children's Communication Checklist, 2nd Edition (CCC-2; Bishop, 2003), and the Gilliam Autism Rating Scale, 3rd Edition (GARS3, Gilliam, 2013).

2.3.2 Experimental Session 1 (Day1:AM)

On the morning of the Day 1, at around 9 am, participants were tested on 25 novel synthesised words (Day1:AM-pre), with this word list going on to be the Trained list for that participant at all subsequent time points. After the task was introduced each item was presented in isolation, with a picture of a robot on the computer screen. Participants were asked to repeat what the robot said, or take a guess, or say that they did not know. The experimenter recorded 'correct' or 'incorrect' with a mouse click, which moved the paradigm on to the next test item without providing feedback for the child. Item order was randomised and no feedback was given during this testing phase. Stimuli were presented and verbal responses recorded by E-Prime2 (Psychology Software Tools, 2012).

After the Day1: AM-pre test, participants completed a training phase. During training, participants heard one novel stimulus item per trial and were asked to perform a 2AFC task with a verbal repetition response. During the presentation of each auditory token two pictures were displayed on the computer screen: one being the target and the second being a distractor with the same number of syllables and the same initial phoneme, for example 'parrot' and 'popcorn' (see Figure 2). The picture onset was aligned to the start of the auditory stimuli and each remained on the screen until the participant made their response, at which point the experimenter marked it as correct or incorrect with a mouse click. The experimenter mouse click triggered participant feedback in the form of a clear auditory token spoken by a British male, followed by the synthesised token again after a 500ms interval. During feedback the target picture remained in the centre of the screen. Each participant completed training with five lists of 25 words, with one of these lists being the participant's "Trained" list; list order and items within lists were randomised during training. Training lasted around 20 minutes including breaks between lists as needed. Feedback was included here as studies have shown that reinforcement facilitates the overnight consolidation of transitive inference (Werchen & Gomez, 2013), and hearing clear then distorted feedback during the perceptual learning of distorted speech markedly facilitates learning (Hervais-Adelman et al., 2008). Task demands were kept minimal, with low working memory requirements.

After training, participants were immediately tested on two lists (Day1:AM-post): the list that they were tested on before training (their Trained list) plus one Novel list. Presentation of these 50 items (25 Novel and 25 Trained) was randomised across the test. At each experimental session participants also completed a psychomotor vigilance test (PVT) based on one developed by Basner and colleagues (Basner, Mollicone & Dinges, 2011), which took around four minutes to complete. During the test, which was presented on a laptop using E-Prime2 software, participants were required to give a button press response as quickly as possible when a star appeared on the screen. The PVT was included to assess sustained attention at each test session, allowing a consideration of fatigue during the evening session which could lead to spurious overnight improvements in performance.

Figure 2 about here

2.3.3 Subsequent experimental sessions

On the evening of Day 1 at around 6 pm, the Day1:PM session was conducted, during which participants were again tested on the synthesised speech stimuli; the test consisted of repeating what the robot said when presented with the participant's Trained list plus one Novel list: a total of 50 items randomly presented. The Day2:AM experimental session, conducted at around 9 am on the second day, and the Follow-Up session, followed exactly the same format as the Day1:PM session but with different Novel lists.

2.4 Sleep measurement

During the night between Day 1 and Day 2, participants had their brain activity recorded with PSG. One of four electronically identical portable recording devices was used, either a Titanium by Embla or a Morpheus by Micromed. Recordings were taken at a sampling frequency of 256 Hz from six locations on the scalp (C3/C4/F3/F4/O1/O2), plus lower left and upper right EOG, and two EMG channels on the chin. The ground electrode was placed on the forehead and Cz acted as an online reference, with offline re-referencing to the contralateral mastoid. Recordings were made in RemLogic 3.4.

Ethical approval for this study was granted by the Research Ethics Committee in the Department of Psychology at the University of York. All parents provided informed written consent for their children to take part and all children provided informed oral assent on the first day of testing and before PSG.

3.0 RESULTS

3.1 Behavioural data analysis

Data can be found on the Open Science Framework at https://osf.io/82eqm/files/. Data were analysed using R (R Core Team, 2017), with the 'lme4' package (Bates, Maechler & Bolker, 2012) with plots made using the 'ggplot2' package (Wickham, 2016). Three binomial logistic mixed effects models are presented with accuracy as the dependent variable (see Table 3 for performance descriptives). Models were fitted in two stages. A backward model selection procedure was adopted to establish a parsimonious fixed effects structure, starting with a maximal fixed effects structure (i.e., simple fixed effects and all interaction terms), along with random intercepts. Fixed effects were then individually knocked down starting with highest order interactions. The removal of each fixed effect was assessed via likelihood ratio tests, and the removal of a fixed effect was justified if there was no evident reduction in model fit ($p>.2$). At each stage, the fixed effects that contributed least to model fit were removed first (largest *p*-value via likelihood ratio test). Having established which simple fixed effects and interactions contributed to model fit, random intercepts were justified. Finally, random slopes were added one-by-one to see if each alone or in combination made a difference to the fit of the model under a liberal criterion of $p<.2$ (Bates, Kliegl, Vasishth, & Baayen, 2015) compared to the fixed effects and intercepts only model. Slopes were built up in stages, with the slope that contributed most to model fit being kept at each stage. The best fitting models are described below for: 1) data spanning Day1:AM-pre and Day1:AM-post (the 'Training Model'); 2) data describing the time-course of performance at 0, then approximately 12 and 24 hours after training (Day1:AM-post, Day1:PM, Day2:AM; the 'Time-course Model'); and 3) data from the Follow-Up session (the Follow-up model).

For each model, Session and Autism Index Group (AI Group: High AI vs. Low AI) were entered as factorial predictors. AI Group was coded using Simple Coding (Low AI -0.5, High AI 0.5), and Language Composite (Language) as a continuous predictor, with this measure being scaled and centred. The Language Composite was formed from an average of each child's standard scores over six measures of language ability: BPVS-3 (Dunn et al., 2009); Word Definitions BAS3 (Elliott & Smith, 2011); Recalling Sentences subscale from the CELF-4 (Semel et al., 2006); Elision, RAN Digits and Non-Word Repetition from the CTOPP2 (Wagner et al., 2013). RAN letters was not used as nine children were not familiar enough with the names of the letters to complete the task without resorting to letter sounds, such that it could not be considered a test of phonological access for those children. For the TimeCourse and Follow-up models, Condition (Novel vs Trained) was entered as a factorial predictor using Simple Coding (Novel -0.5, Trained 0.5). Intercepts for Participants and Items were included as random effects, along with by-Item random slopes for the effects of Session, Language and Autism Index, and by-Participant slopes for Session.

In each model, influential cases were detected using the package influence.ME (Nieuwenhuis, Pelzer & te Grotenhuis, 2012) to calculate DFBETAS (Belsley, Kuh & Welsch, 1980) for each of the simple fixed effects and their interactions in the final models. Z-scores were calculated from DFBETAS and participants were removed from the model if they had z-scores more extreme than +/-3.29 for any significant fixed effect or interaction (two participants from the High AI group were removed from the Training model, three from the Low AI group from the Time-course model and two High AI and one from the Low AI Group were removed from the Follow-Up model).

3.3.1 The Training Model

Details of the best fit Training Model are given in Table 4. The fixed effects of Session (Day1:AM-pre vs. Day1: AM-post coded using Simple Coding: Day1:AM-pre, -0.5, Day1:AM-post, 0.5) and Language significantly contributed to the model fit, with accuracy on Novel items post-training (Figure 3a) being better than accuracy during the pre-training test, and better performance on the Language Composite predicting better overall performance in the Day1:AM session (Figure 3b). No interactions between fixed effects significantly contributed to the model fit. Training therefore successfully improved performance for the sample as a whole and while language ability predicted performance on the task, it did not predict the benefit of training.

Tables 3 and 4 and Figure 3 about here

3.1.2 Time-course Model

We next analysed the time-course of performance on trained and novel items after training with degraded speech. Session (Day1:AM-post, Day1:PM, Day2:AM) was entered as a factorial predictor with three levels, therefore planned contrasts were coded using Forward Difference Coding (UCLA Statistical Consulting Group) to include a comparison between the Day1:AM and Day1:PM sessions (daytime change: Day1:AM-post = 2/3, Day1:PM = -1/3, Day2:AM = -1/3) and the Day1:PM vs Day2:AM sessions (overnight change: Day1:AM-post = 1/3, Day1:PM = 1/3, Day2:AM = -2/3). It was hypothesised, in line with previous research with adults, that performance on Novel items (indicating generalisation) would decline between Day1:AM-post (0 hrs) and Day1:PM (12 hrs) then improve at the Day2:AM session (24 hrs) after a night of sleep. In comparison, Trained items were expected to show maintained performance at all points after training. Overall performance was hypothesised to be predicted by language ability while those in the High AI group were predicted to show poorer performance on the Novel condition and to demonstrate less improvement in performance overnight (Day1:PM to Day2:AM).

Over the wake retention period (Day1:AM-post to Day1:PM), overall performance did not significantly change (Day1:AM-post mean = 0.706, SD = 0.171; Day1:PM mean = 0.694, SD = 0.189). By contrast, performance was observed to significantly improve over the course of the sleep period (Day2:AM mean = 0.737, SD = 0.183). As shown in Table 5, Condition (Novel vs Trained) also contributed to model fit, with performance on the Trained condition (mean = 0.820, SD = 0.125) being substantially better than performance on the Novel condition (mean = 0.604, SD = 0.165), though no interaction between Condition and Session was observed . The significant contribution of the Day1:PM vs. Day2:AM comparison is consistent with the hypothesis that sleep is associated with phonological learning on this task (see Figure 4), and the lack of interaction with Condition indicates that both Novel and Trained items benefitted. As we saw with the Training Model, children who showed better language ability also performed better on the task overall, with Language contributing significantly to model fit. A two-way interaction between Condition and Language also emerged. This interaction was driven by a tendency towards ceiling effects in the Trained condition for children with better language ability (evident in Figure 5). This interpretation is supported by significant heteroscedasticity in the Trained condition but not in the Novel condition, as demonstrated by non-constant variance score tests on linear regression models predicting overall performance in each model by Language (Trained: χ^2 (1) = 157.3, p < .001; Novel: χ^2 (1) = 2.2, p = .142). An interaction between Condition, Language and Group also emerged, as shown in Figure 5, which suggests that language ability predicts performance better in the Trained condition than the Novel condition for those with low autism symptomology. This interpretation was supported using the package *emmeans* (Lenth, 2019): we found that accuracy as a function of Language composite differed between Conditions for the Low AI group, while this was not true for the High AI group (Low AI: Novel – Trained estimate = -0.485, SE = 0.150, z ratio = -3.230, p = .0012; High AI: Novel – Trained estimate = -0.076, SE = 0.106, z ratio = -0.717, p = .4734, with Tukey correction for multiple comparisons). This seems to be driven by the particularly shallow slope seen for Novel items in the Low AI group – here, having lower language ability does not confer a disadvantage on the Novel condition. Autism Index did not interact with Condition, suggesting that the High AI group did not show a specific deficit in phonological generalisation on this task. We consider change in performance overnight in relation to the sleep variables of interest in more detail below.

Table 5 & Figures 4 & 5 about here

3.1.3 Attention

The PVT data were analysed by dividing each response time (RT) in milliseconds by 1,000 then reciprocally transforming (1/RT: 'response speed', in line with Basner & Dinges, 2011) before calculating averages for each participant over the Day1:AM, Day1:PM and Day2:AM sessions (see Table 3). RTs were excluded from this process if they were shorter than 100ms. A mixed ANOVA with Session (Day1:AM, Day1:PM, Day2:AM) and Group (by Autism Index) revealed a main effect of Session ($F(2, 146) = 12.69$, $p<0.001$) which was driven by a difference between Day1:AM (re-transformed mean = 399.77ms, SD = 250.57) and Day1:PM (re-transformed mean = 436.67ms, SD = 384.50; $p < .001$) and between Day1:AM and Day2:AM (Day2:AM re-transformed mean = 460.95ms, SD = 406.92; $p = .001$). No main effect of group or interaction between group and session was observed. We also analysed the number of lapses observed at each session, defined as the number of reaction times greater than 500 ms. Lapses showed a main effect (correcting for violation of sphericity where appropriate) of Session ($F(1.7, 128.3)=24.875$, $p < .001$) driven by a difference between Day1:AM (mean = 13.16, SD = 14.93) and Day1:PM (mean = 19.53, SD = 14.74) at $p < .001$ as well as between Day1:AM and Day2:AM (mean =20.97, SD = 18.69) at $p < .001$. A main effect of Group was observed in the lapse data ($F(1,74) = 4.755$, $p = .032$), as well as a marginally significant interaction between Session and Group (F (1.7, 128.3) = 3.217, p = .050, driven by a difference between groups only in Session 3 (t(75)=2.718, p = .008) (Low AI mean = 16.70, SD = 16.36, High AI mean = 27.90, SD = 20.02). While the faster reaction times and fewer lapses at Session 1 likely indicates that children tired of the repetitive task (as supported by feedback from children), the lack of difference between Day1:PM and Day2:AM indicates that overnight improvement in performance cannot be attributed to enhanced attention in the morning.

3.1.4 Follow-up Model

Finally, we considered performance at the follow-up test approximately four weeks after initial training (Follow-Up). The follow-up was completed by 64 children, an average of 32.7 days (min = 25, max = 47, SD = 5.9) after training. Follow-Up performance was not compared to prior sessions as not all children completed the follow-up session, although broadly speaking, performance at this test point suggests that learning was well maintained in the sample. As shown in Table 6, Condition and Language both contributed to model fit, supporting findings from the Time-course model that the Trained condition was easier for children (Novel mean = 0.650, SD = 0.477; Trained mean = 0.847, SD = 0.360) and that those with stronger language skills were able to perform at a higher level. An interaction between Condition, Language and Group also emerged, as in the Time-course model. Here, *emmeans* revealed a somewhat different pattern to that seen in the Time-course model: with the Novel and Trained slopes becoming more similar over time for the Low AI group and more distinct for the High AI group (Low AI: Novel – Trained estimate = 0.079, SE = 0.202, z ratio = 0.390, p = .6965; High AI: Novel – Trained estimate = -0.477, SE = 0.182, z ratio = -2,623, p =

.0087, with Tukey correction for multiple comparisons). Four weeks after training, low language scores were less of a disadvantage on the Novel condition for the high AI group (see Supplementary materials SM1 for illustration).

In each of the mixed effects models presented here, both Language and AI Group have been included; as the AI groups differ with respect to language ability (see Table 1), this is a potential confound. In order to make sure that any effects of group were not hidden by those children with primary language difficulties who were included in the High AI group on account of having a GARS3 score within the 'very likely' range, we plotted the performance of the five children who did not have a current or pending diagnosis of ASD relative to the rest of the sample. The graphs shown in Supplementary Materials (SM2/3) suggest that these children were spread across the range of performance on this task. This check, in combination with the fact that we see consistently strong relationships between performance accuracy and language ability, but never AI group, suggests that autism symptomatology is not contributing in any meaningful way to performance or performance change.

Table 6 about here

3.2 Sleep data

3.2.1 Staging of EEG data

Each dataset was hand-scored independently by two out of a pool of three researchers in accordance with the American Association of Sleep Medicine rules for children (AASM, 2016). Independent scoring resulted in 82.9% concordance. Where scorers disagreed on the staging of ten or more consecutive 30 second epochs, the data were re-considered and if an agreement could not be reached the staging given by the designated first scorer was used. Of the 77 participants who contributed behavioural data in this study, 54 contributed enough stage-able PSG data to identify a sufficient amount of both REM and NREM sleep for the extraction of sleep parameters (35 male, 29 female, with a mean age of 121.17 months (SD = 16.40)). Of these, 33 participants were from the Low AI group, and 21 from the High AI group. The loss of PSG data is primarily due to the loss of key electrodes over the course of the night (particularly towards the morning), which impacted on the quality of REM data towards the end of recordings.

To ensure that overnight EEG measurements were representative of a normal night of sleep, participants were given an Ambulatory Monitoring Inc. actigraph watch to wear for approximately four nights including the night of learning between the Day1:PM and Day2:AM. Some participants chose to wear the watch for longer. For the 54 participants who contributed staged EEG data, on average the watch was worn for 4.56 nights (min = 3, max = 7), with an average of 3.35 nights (min = 0, max = 5) when the child was in their normal bed-time routine. Children were taken to be in their normal routine on a week night during term time; for the two children who wore the actigraph watch and were home schooled, any night of the week was counted as routine. We compared total sleep time on the night of learning with an equivalent night (in or out of routine): overall the participants did not differ between the two nights (p = 0.506), and split by AI group there were no differences on this measure either (Low AI group, learning night mean = 481.89 minutes, comparison night mean = 463.96 minutes, p = 0.344; High AI group, learning night mean = 445.31 minutes, comparison night mean = 446.94 minutes, p = 0.957). We can therefore assume that the EEG measurements taken on the night of learning were reasonably representative of sleep for our sample.

3.2.2 Spindle density and power calculations

Spindles were identified and counted using an algorithm written by Tsanas and Gifford (2015), which uses a continuous wavelet transform to identify characteristic patterns of activity between 10 and 15Hz. Absolute power was calculated in Matlab (MathWorks, 2017) at each scalp electrode for fast (10.00 - 12.49Hz) and slow (12.50 - 14.99Hz) spindle ranges, Delta (0.30 - 3.99Hz), Alpha (9.00 - 12.99Hz) and Beta (13.00 -35.00Hz); natural log transformations were applied to all power variables before analysis. In order to maximise usable datasets we opted to analyse the first three hours of NREM data (Stage 2 and SWS) and the first 1.25 hours of REM data. For the 27 children who required the least artefact rejection over the course of the night, the correlation between absolute power in NREM stages in the first three hours and all night was r = 0.91 for the slow spindle range (10.00 – 12.49Hz) frontally and r = 0.91 for the fast spindle range (12.50-14.99Hz) centrally; for central REM theta power and between the first 1.25 hours and all night r = 0.95. Children were included in the analysis of spindles and power if they contributed all parameters to both REM and NREM datasets; on these grounds 48 children were included, 31 from the Low AI group, and 17 from the High AI group. For spindle and power analyses, data were extracted from C4 and F4 where possible, but in 11 cases, C3 was deemed to be the cleaner channel and in 8 cases, F3 was taken.

The hypothesis-driven predictors included were: central spindle density, frontal slow spindle power (10.00 - 12.49Hz), and central fast spindle power (12.50 - 14.99Hz) for Stage 2 and Stage 3 separately, SWS frontal Delta power (0.30 – 3.99Hz) and central REM Theta power; Autism Index, Language and Age in months were also included. Relationships between overnight change in accuracy and characteristics of sleep architecture were considered using linear regression. The leaps package (Lumley, 2017) was used to exhaustively search for the subset of variables that provided the highest $AdjR^2$, with these variables then being used to predict change in performance for each Condition.

None of the log transformed sleep variables considered here differed between AI groups (see Table 7). That being said, in a partially overlapping sample of 17 children with typical language ability and a diagnosis or pending diagnosis of ASD from the same cohort, presented in a separate paper (Fletcher et al., submitted), did show significantly reduced overall spindle power across stages 2&3 when compared to 28 typically developing controls. We present sleep data from all the children who contributed data to the SleepSmart sample and provide group differences for all sleep parameters considered across each paper via the Open Science Framework at https://osf.io/82eqm/files/.

In the case of the Novel condition, the selected subset of predictors consisted of central Stage 2 spindle density, Stage 2 frontal slow spindle power, Stage 3 frontal delta, central REM theta, Age. A model with these predictors was able to significantly predict overnight change in performance on the Novel condition, $AdjR^2 = 0.225$, $F(7,39) = 2.909$, $p = 0.0151$, with central spindle density in Stage 2 (B = 0.009) and Stage 3 (0.047),frontal slow spindle power in Stage 2 (B = -0.071) and Stage 3 (-0.092) frontal delta power in Stage 3 (0.093,central REM theta (B = 0.173) and Age (-0.002) emerging as significant predictors (see Table 8). Variance inflation factors (VIF) were checked and did not exceed 3.8, VIF for REM theta power was 1.4. One participant was removed as overly influential based on DFBETAS. These data suggest that REM sleep contributes to the generalisation of phonological learning in this task, as supported by REM theta power being a significant predictor of overnight change in performance on the Novel condition when entered alone, B = 0.122, t = 2.278, p = .0276 (see Figure 6).

For overnight changes in Trained performance (see Table 8), the selected subset of variables consisted only of Language and Stage 2 central fast spindle power. These variables did not predict change, AdjR^2 = 0.062, F(2,45) = 2.55, *p* = .089, although Language Composite score did emerge as a unique predictor of overnight change (B = -0.001). Looking at the extent to which performance at the Day1:PM session predicts performance at the Day2:AM session, we might expect this stark contrast between the predictive ability of sleep parameters across the two conditions. For the Trained condition, performance at the Day2:AM session is well predicted by performance the evening before during the Day1:PM session (R^2 = 0.789), while predictive power for the Novel condition is markedly lower (R^2 = 0.385), leaving considerably more variability to explain for the Novel condition.

Tables 7 & 8 & Figure 6 about here

<u>4.0 Discussion</u>

In this study we charted the time-course of phonological learning and generalisation over the course of 24 hours in a sample of children who varied with respect to structural language ability and autism symptomatology. Training was carried out with text-to-speech synthesised speech tokens, which required children to re-map phonological representations to include new exemplars for existing phonological categories. On the night following training children wore polysomnography sensors to measure nocturnal sleep parameters which may be associated with the consolidation of new phonological information.

Successful performance on this task required children to shift decision boundaries in the identification of phonemes, somewhat like learning to listen to an unfamiliar speaker with a strong accent. The listener's task is further complicated in the case of synthetic speech as re-mapping rules are not systematic: making adjustments for one phoneme does not help listeners tune in to another. When tested on novel items, the task required children to transfer their phonological learning to new tokens, necessitating phoneme-by-phoneme recognition rather than word-level auditory pattern recognition.

Training was effective in our paradigm, with children showing a substantial average improvement of around 30% on novel tokens (concrete nouns) pre- to post-training. This training effect supports the effectiveness of clear and degraded feedback on performance (Hervais-Adleman et al., 2008). Over the course of the day following training, performance on the task as a whole did not change significantly. This was contrary to expectations based on Fenn and colleagues' adult data (Fenn et al., 2013), which showed a dip in performance on a generalisation task over the course of a day; though the current task also differed from that of Fenn and colleagues in important ways (as outlined in the Introduction). The lack of a significant reduction in performance may, however, represent a genuine developmental effect as it is consistent with literature showing inter-session decline in performance for adults but not children on linguistic tasks including artificial grammar learning (Ferman & Karni, 2010) and non-word repetition (Bishop, Barry & Hardiman, 2012). However, in order to determine whether differences in methodology or sample characteristics explain our results, children, adolescents and adults would need to be tested using the same procedure.

Overnight, we saw an overall improvement in performance. This pattern could not be attributed to a sleep debt in the evening affecting attentional control, as performance on the PVT did not differ between sessions before and after sleep (Day1:PM vs Day2:AM). Testing in the morning was conducted after children arrived at school, long enough after waking to avoid effects of sleep inertia (see Trotti, 2017), such that the decline seen in PVT reaction time seen after the first experimental session is likely explainable by task fatigue. No interaction emerged between overnight change and condition, suggesting that sleep promotes phonological learning in children for both trained items and generalisation to novel items. This finding is a deviation from the specific effect of sleep found for the generalisation of phonological information in adults (Fenn et al., 2013). This difference could be attributable to a developmental shift in the influence of sleep on the consolidation of different types of memory, with enhanced benefits of sleep for explicit aspects of task performance (Wilhelm et al., 2013) in children. Alternatively, we could attribute the contrast of our results with Fenn and colleagues to a difference in methodology. Fenn et al. utilised a between-subjects design such that participants in the rote condition only ever experienced rote items in training, while participants in the novel condition experienced a variety of items in training. Here, children were trained on multiple items but tested on both trained *and* novel items at each time point. This suggests that generalisation is likely to contribute to performance in the trained condition as well as the novel condition. According to this explanation, sleep may act preferentially on generalisation, rather than other types of phonological learning in childhood, but our within-participants design could not isolate generalisation.

We hypothesised that performance on both trained and novel items would be associated with REM theta power, and that generalisation would be additionally related to spindle activity and power during Non-REM sleep stages. These hypotheses were based on work by Earle and Myers (2014), suggesting that the exact relationships between sleep characteristics and phonological learning would depend heavily on the nature of the task itself given that phonological learning is not easily classified as either declarative or procedural in nature. As hypothesised, we saw that theta power in REM sleep predicted overnight change in performance on the novel condition. This finding is consistent with an active role for sleep in phonological generalisation, and specifically a role for synaptic consolidation in the type of phonological generalisation shown here. Notably though, we did not find any evidence for a relationship between behavioural change and NREM sleep parameters.

This study is one of a small number to consider the role of sleep in phonological generalisation (Fenn et al., 2013, 2003; Earle & Myers, 2015; Xie & Myers, 2016; Xie, Earle & Myers, 2018). Together, these papers pose the questions: what aspects of phonological generalisation is sleep associated with, and if sleep actively supports such generalisation then what are the mechanisms of that support? In previous work, a consolidation period containing sleep has been shown to improve listeners' ability to generalise perceptual learning across speakers who show phonemic variability (Earle & Myers, 2015; Xie, Earle & Myers, 2016; 2018). In these studies, generalising learning to a new speaker means being able to adjust specific category boundaries to allow for inter-speaker variability, suggesting that sleep is relevant to the abstraction of higher-level category-relevant phonemic information. In the task adopted by Fenn et al (2013), adults were required to use the new phonological mappings to which they had been exposed to understand previously unheard synthesised words. Sleep benefitted the re-combination of those new mappings, but did not support those in the rote-trained condition to extract any higher level information about the synthetic voice to generalise to new words containing previously unheard phonemes. In the current study, the training that children experienced included comprehensive exposure across all phonemes necessary to succeed at test[2]. Children did not have to adapt the new mappings when tested, but rather re-combine them to understand new words (with the exception of allowing for phonological assimilation). Collectively, these results beg the question, what is sleep doing exactly?

The hypothesis that REM sleep might relate to behavioural change on this paradigm was based on the understanding that the task as a whole required participants to shift attention towards relevant acoustic features of speech stimuli in order to learn new phonological mappings. The exact association we found, however, was between theta power in REM sleep and the ability to *recombine* those newly-mapped phonological categories. Unfortunately, we were unable to properly assess how specific this relationship was as overnight change in performance on trained items was not associated with any sleep variables. The most likely reason for this is that performance after sleep was very well predicted by pre-sleep performance, and for children with superior language ability, performance neared ceiling levels after sleep such that inter-participant variability in overnight change may have been curtailed, reducing the likelihood of seeing relationships with sleep parameters. Change in performance on the trained condition was only predicted (negatively) by language ability, with children who had poorer language ability also having more room left to improve on the task. This tendency toward ceiling effects in the trained condition on day two may also have prohibited an interaction between condition and overnight change which, had it emerged, would have demonstrated a sleep advantage for word-level auditory pattern recognition in addition to generalisation.

That sleep plays a role in phonological generalisation in children adds to our

[2] During training all children were exposed to all 44 phonemes in the English language, with the exceptions that one group did not hear /ʒ/ and two groups did not hear /ʊ/.

knowledge and understanding of the mechanisms of sleep and its role in the consolidation of new knowledge at this age. Here, sleep can be seen to support perceptual learning in the phonological domain, to help the system remain stable and flexible as it encounters new items, thereby supporting adaptation to the environment. Interestingly, over the course of four weeks learning remained relatively stable, with performance at the follow-up session showing the same pattern as after encoding; performance level also appeared stable (though this was not tested statistically), suggesting that perceptual learning in the phonological domain shows good retention over weeks despite no intervening practice or relevance. Similar stability of perceptual learning after training with synthesised speech has been demonstrated in adults (Schwab, Nusbaum & Pisoni, 1985).

This study aimed to consider phonological learning in children who differed with respect to the stability and flexibility of phonological representations. It was hypothesised that children with poorer structural language would perform less well than their peers overall and show a slower rate of learning on account of having less stable phonological representations to map new exemplars on to. In reality, many different aspects of the language system could lead to poorer performance on this task. For example, vocabulary knowledge may impact on phonological processing given that semantic and phonological representations are inter-dependent (see McClelland, Mirman & Holt, 2006). We tried to ensure that all items would be familiar to all children, but the extent of familiarity, the depth of semantic knowledge and the speed of lexical retrieval is likely to have varied considerably in this sample. Unfortunately, we were unable to verify this given the large number of items presented to participants over the course of the study. Language ability emerged as a strong predictor of overall task performance in all models, but did not predict change in performance, with the exception of overnight change in the trained condition, as discussed above.

In individuals with high autism traits, we hypothesised we would see poorer performance on novel items compared to trained items, reflecting a hypothesised tendency in those with ASD to allocate greater attentional resources to features that are unique to individual items, and less to features common across items compared to typically developing peers (Plaisted, 2001). We did not find an overall group difference here; indeed, phonological learning more broadly is often a relative strength in the language profiles of children with ASD, with some studies showing enhanced performance on tasks that demand the learning of new phonological forms (e.g., Henderson et al., 2014; Norbury et al., 2012). However, we did observe a deficit in generalisation (performance on the Novel condition) for those individuals with high autism symptomology *and* low language ability. Language ability constrained performance on the novel items for those with high autism traits. If difficulties with generalisation do exist in this population, enhanced phonological skills may act as a protective factor in this domain for some individuals. Finally, no group differences were observed with respect to the specific sleep parameters of interest between children with high and low autism symptomatology in this sample (though see https://osf.io/82eqm/files/ for sleep results from the full sample). Given that these sleep parameters explained variance in overnight change in generalisation, it is perhaps not surprising that group differences in behaviour did not emerge here.

4.1 Limitations and conclusions

The findings of this study should be considered in the light of its main limitation: the nature of the atypical samples recruited to this study. Children recruited on account of falling along the autism spectrum did not have severe symptomatology. This recruitment bias was expected given that children with severe ASD symptoms often show hypersensitivity to tactile stimuli, in particular touching of the head or body (see Marco, Hinkley, Hill & Nagarajan, 2011 for a review), such that the overnight electrophysiological measurement would be difficult to tolerate for many. We were also keen to only involve children who we felt confident could give informed oral assent to the procedure. The future inclusion of children with more severe symptoms in a behavioural study of phonological generalisation could address more clearly the flexibility of phonological representations in this population. We were also only able to include a relatively small number of children here with severe language difficulties due to issues with recruitment. This is likely to have limited the extent to which stability of phonological representations varied over the sample. Children with language disorders are believed to show some degree of behavioural sleep problems (Dominick et al., 2007; Botting & Baraka, 2017), but no studies have examined the architecture of sleep in this population in over 20 years (Duvelleroy-Hommet et al., 1995; Picard et al., 1998). More thorough consideration of how phonological learning relates to sleep in this population may therefore be crucial in trying to understand the long-term nature of phonological development in these children.

This study considered the role of sleep in phonological learning in children who varied as a function of structural language skill and autism symptomatology. We showed that sleep is associated with phonological learning in childhood, with phonological generalisation being supported by theta power in REM sleep. Language skill was found to predict overall task performance, although the role of REM sleep did not differ as a function of language ability. This work adds to a growing literature exploring the importance of sleep for the stability of new learning and the integration of new representations into existing networks in childhood.

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References

Achenbach, T.M., & Edelbrock, C. (1983). *Manual for the Child Behavior Checklist and Revised Child Behavior Profile*. Burlington,VT: University of Vermont Department of Psychiatry, 1983. Pp. 230.

American Association of Sleep Medicine. (2016). *The AASM Manual for the Scoring of Sleep and Associated Events: Rules, Terminology and Technical Specifications*. AASM Darien, IL.

Anthony, J. L., Williams, J. M., Aghara, R. G., Dunkelberger, M., Novak, B., & Mukherjee, A. D. (2010). Assessment of individual differences in phonological representation. *Reading and Writing, 23*, 969-994.

The Audacity Team (1999-2016). Audacity, version 2.1.3, Audio editor and recorder. http://audacityteam.org/

Basner, M., & Dinges, D. F. (2011). Maximising sensitivity of the psychomotor vigilance task (PVT) to sleep loss. *Sleep, 34* (5), 581-591.

Basner, M., Mollicone, D., & Dinges, D. F. (2011). Validity and sensitivity of a brief psychomotor vigilance test (PVT-B) to total and partial sleep deprivation. *Acta Astronautica, 69*, 949–959.

Bates, D., Mächler, M., Bolker, B. M., & Walker, S. C. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software, 67* (1): https://doi.org/10.18637/jss.v067.i01

Bates, D., Maechler, M., & Bolker, B. (2012). *lme4: Linear Mixed-Effects Models Using S4 Classes* (R Package Version 0.999999-0). http://cran.r-project.org/web/packages/lme4/index.html

Batterink, L., Oudiette, D., Reber, P. J., & Paller, K. A. (2014). Sleep facilitates learning a new linguistic rule. *Neuropsychologia, 65,* 169-179.

Batterink, L. J., & Paller, K. A. (2017). Sleep-based memory processing facilitates grammatical generalization: evidence from targeted memory reactivation. *Brain and Language, 167*, 83-93.

Belsley, D., Kuh, E., & Welsch, R. (1980). *Regression diagnostics. Identifying influential data and sources of collinearity*. Wiley, 1980. [p.39, 40, 43].

Bishop, D. V. M. (2003). *The Children's Communication Checklist, 2nd Edition*. London: Pearson.

Bishop, D. V., Barry, J. G., & Hardiman, M. J. (2012). Delayed retention of new word-forms is better in children than adults regardless of language ability: a factorial two-way study. *PLoS One*, 7 (5): e37326.

Botting, N., & Baraka, N. (2017). Sleep behaviour relates to language skills in children with and without communication disorders*. International Journal of Developmental Disabilities*, 1-6. https://doi.org/10.1080/20473869.2017.1283766

Brysbeart, M., & New, B. (2009). Moving beyond Kučera and Francis: A critical evaluation of current word frequency norms and the introduction of a new and improved word frequency measure for American English. *Behaviour Research Methods*, 41 (4), 977-990.

Brysbaert, M., Warriner, A. B., & Kuperman, V. (2014). Concreteness ratings for 40 thousand known English word lemmas. *Behavioural Research Methods, 46* (3), 904-911.

Chang, E. F., Rieger, J. W., Johnson, K., Berger, M. S., Barbaro, N. M., & Knight, R. T. (2010). Categorical speech representation in human superior temporal gyrus. *Nature Neuroscience, 13* (11), 1428-1432.

Coady, J. A., Kluender, K. R., & Evans, J. L. (2005). Categorical perception of speech by children with specific language impairments. *Journal of Speech Language and Hearing Research, 48* (4), 944-959.

Collet, G., Schmitz, R., Urbain, C., Leybaert, J., Colin, C., & Peigneux, P. (2012). Sleep may not benefit learning new phonological categories. *Frontiers in Neurology*, https://doi.org/10.3389/fneur.2012.00097

Constantino, J. N., Yang, D., Gray, T. L., Gross, M. M., Abbacchi, A. M., Smith, S. C., Kohn, C. E., & Kuhl, P. K. (2007). Clarifying the associations between language and social development in autism: a study of non-native phoneme recognition. *Journal of Autism and Developmental Disorders, 37* (7), 1256-1263.

Cox, R., Hofman, W. F., & Talamini, L. M. (2012). Involvement of spindles in memory consolidation is slow wave sleep-specific. *Learning and Memory, 19*, 264-267.

Crane, L., Chester, J. W., Goddard, L., Henry, L. A., & Hill, E. (2015). Experiences of autism diagnosis: A survey of over 1000 parents in the United Kingdom. *Autism, 20* (2), 153-162.

Díaz-Román, A., Zhang, J., Delorme, R., Beggiato, A., & Cortese, S. (2018). Sleep in youth with autism spectrum disorders: systematic review and meta-analysis of subjective and objective studies. *Evidence-Based Mental Health, 21* (4),

Diekelmann, S., & Born, J. (2010). The memory function of sleep. *Nature Reviews Neuroscience, 11* (2), 114-126.

Dominick, K. C., Ornstein Davis, N., Lainhart, J., Tager-Flusberg, H., & Folstein, S. (2007). Atypical behaviors in children with autism and children with a history of language impairment. *Research in Developmental Disabilities, 28,* 145–162.

Dunn, L. M., Dunn, D. M., Styles, B., & Sewell, J. (2009). *The British Picture Vocabulary Scale III – 3rd Edition*. London: GL Assessment

Duvelleroy-Hommet, C., Billard, C., Lucas, B., Gillet, P., Barthez, M. A., Santini, J. J., Degiovanni, E., Henry, F., De Toffol, B., Autret, A. (1995). Sleep EEG and developmental dysphasia: lack of a consistent relationship with paroxysmal EEG activity during sleep. *Neuropediatrics, 26* (1), 14- 18.

Earle, F. S., Landi, N., & Myers, E. B. (2018). Adults with Specific Language Impairment fail to consolidate speech sounds during sleep. *Neuroscience Letters, 666*, 58-63.

Earle, F. S., Landi, N., & Myers, E. B. (2017). Sleep duration predicts behavioural and neural differences in adult speech sound learning. *Neuroscience Letters*, *636*, 77-82.

Earle, F. E., & Meyers, E. B. (2014). Building phonetic categories: an argument for the role of sleep. *Frontiers in Psychology, 5*, Article 1192.

Earle, F. E., & Meyers, E. B. (2015). Overnight consolidation promotes generalization across talkers in the identification of non-native speech sounds. *Journal of the Acoustical Society of America, 137* (1): EL91-7. https://doi.org/10.1121/1.4903918

Eisner, F., & McQueen, J. M. (2006). Perceptual learning in speech: stability over time. *Journal of the Acoustical Society of America, 119* (4), 1950-1953.

Elliott, C. D., & Smith, P. (2011). *The British Ability Scales, 3rd Edition*. London: GL Assessment.

Elrod, M. G., & Hood, B. S. (2015). Sleep differences among children with autism spectrum disorders and typically developing peers: a meta-analysis. *Journal of Developmental and Behavioral Pediatrics, 36* (3), 166-177.

Fenn, K. M., Nusbaum, H. C., & Margoliash, D. (2003). Consolidation during sleep of perceptual learning of spoken language. *Nature, 425*, 614-616.

Fenn, K. M., Margoliash, D., Nusbaum, H. C. (2013). Sleep restores loss of generalised but not rote learning of synthetic speech. *Cognition, 128*, 280-286.

Ferman, S., & Karni, A. (2010). No childhood advantage in the acquisition of skill in using an artificial language rule. *PLOS one, 5* (10): e13648

Francis, A. L., Baldwin, K., & Nusbaum, H. (2000). Effects of training on attention to acoustic cues. *Perception and Psychophysics, 62* (8), 1668-1680.

Gagnon, R. T. (1978). Votrax Real Time Hardware for Phoneme Synthesis of Speech. *Proceedings of the International Conference on Acoustics, Speech and Signal Processing (ICASSP), 78,* 175-178.

Gilliam, J. E. (2013). *Gilliam Autism Rating Scale, 3rd Edition (GARS3)*. London: Pearson.

Godbout, R., Bergeron, C., Limoges, E., Stip, E., & Mottron, L. (2000). A laboratory study of sleep in Asperger's Syndrome. *NeuroReport, 11* (1), 127-130.

Hazan, V. L., & Barett, S. (2000). The development of phonemic categorization in children aged 6-12. *Journal of Phonetics, 28* (4), 377-396

Henderson, L., Devine, K., Weighall, A., & Gaskell, G. (2015). When the Daffodat flew to the intergalactic zoo: off-line consolidation is critical for word learning from stories. *Developmental Psychology, 51* (3), 406-417.

Henderson, L.M., Powell, A., Gaskell, M.G., & Norbury, C. (2014). Learning and consolidation of new spoken words in autism spectrum disorder. *Developmental Science*, 17, 858-71.

Henderson, L., Weighall, A., & Gaskell, G. (2013). Learning new vocabulary during childhood: effects of semantic training on lexical consolidation and integration. *Journal of Experimental Child Psychology, 116* (3), 572-592.

Hervais-Adleman, A., Davis, M. H., Johnstrude, I. S., & Carlyon, R. P. (2008). Perceptual learning of noise vocoded words: effects of feedback and lexicality. *Journal of Experimental Psychology, Human Perception and Performance, 34* (2), 460-474.

Järvinen-Pasley, A., Wallace, G. L., Ramus, F., Happé, F., & Heaton, P. (2008). Enhanced perceptual processing of speech in autism. *Developmental Science 11*, (1), pp 109–121.

Joanisse, M. F. (2004). Specific language impairments in children: Phonology, semantics and the English past tense. *Current Directions in Psychological Science, 13* (4), 156-160.

Joanisse, M. F., & Seidenberg, M. S. (2003). Phonology and syntax in specific language impairment: Evidence from a connectionist Model. *Brain and Language, 86*, 40-56.

Kleinschmidt, D. F., & Jaeger, T. F. (2015). Robust speech perception: Recognize the familiar, generalize to the similar, and adapt to the novel. *Psychological Review, 122*(2), 148-203.

Knowland, V. C. P., Evans, S., Snell, C., & Rosen, S. (2016). Visual speech perception in children with language learning impairments. *Journal of Speech, Language and Hearing Research, 59*, 1-14.

Kuperman, V., Stadthagen-Gonzalez, H., & Brysbaert, M. (2012). Age-of-acquisition ratings for 30,000 English words. *Behavioural Research Methods, 44* (4), 978-990.

Latchourmane, C. V., Ngo, H. V., Born, J., & Shin, H. S. (2017). Thalamic spindles promote memory formation during sleep through triple phase-locking of cortical, thalamic, and hippocampal rhythms. *Neuron*, 95 (2), 424-435.

Length, R. (2019). emmeans: Estimated Marginal Means, aka Least-Squares means. R package version 1.3.5. https://CRAN.R-project.org/package=emmeans

Liberman, A. M., Harris, K. S., Hoffman, H. S., & Griffith, B. C. (1957). The discrimination of speech sounds within and across phoneme boundaries. *Journal of Experimental Psychology, 54*, 358.

Limoges, E., Mottron, L., Bolduc, C., Berthiaume, C., & Godbout, R. (2005). Atypical sleep architecture and the autism phenotype. *Brain, 128*, 1049–1061.

Lumley, T; based on Fortran code by Alan Miller. (2017). *Leaps: Regression on subset selection. R package version 3.0*. https://CRAN.R-project.org/package=leaps

Maillart, C., Schelstraete, M.-A., & Hupet, M. (2004). Phonological representations of children with SLI : a study of French. *Journal of Speech, Hearing and Language Research, 47,* 187 - 198.

Marco, E. J., Hinkley, L. B., Hill, S. S., & Nagarajan, S. S. (2011). Sensory processing in autism: a review of neurophysiologic findings. *Pediatric Research, 69* (5). 48R-54R.

Maski, K., Holbrook, H., Manoach, D., Hanson, E., Kapur, K., & Stickgold, R. (2015). Sleep dependent memory consolidation in children with Autism Spectrum Disorder. *Sleep, 38* (12), 1955-1963.

MathWorks Inc. (2017). MATLAB Release 2017a. The MathWorks Inc, Natick, Massachusetts, United States.

McClelland, J. L., Mirman, D., & Holt, L. L. (2006). Are there interactive processes in speech perception? *Trends in Cognitive Science, 10* (8), 363-369.

Mielke, J., Nielsen, K., & Magloughlin, L. V. (2013). Phonetic imitation by individuals with Autism Spectrum Disorders: Investigating the role of procedural and declarative memory. *Proceedings of Meetings on Acoustics, 19,* 060142.

Mines, M. A., Hanson, B. F., & Shoup, J. E. (1978). Frequency of occurrence of phonemes in conversational English. *Language and Speech, 21* (3), 221-241.

Nieuwenhuis, R., Pelzer, B., & te Grotenhuis, M. (2012*). influence.ME: tools for detecting influential data in mixed effects models.* URL: http://CRAN.P-project.org/package=influence.ME. R package version 0.9 [p.38].

Norbury, C. F., Griffiths, H., & Nation, K. (2010). Sound before meaning: word learning in autistic disorders. *Neuropsychologia, 48* (14), 4012-4019.

Ohayon, M. M., Carskadon, M. A., Guilleminault, C., & Vitiello, M. V. (2004). Meta-analysis of quantitative sleep parameters from childhood to old age in healthy individuals: developing normative sleep values across the human lifespan. *Sleep, 27* (7): 1255-1273.

Owens, J. A., Spirito, A., & McGuinn, M. (2000). The Children's Sleep Habits Questionnaire (CSHQ): psychometric properties of a survey instrument for school-aged children. *Sleep, 23* (8), 1043-1051.

Picard, A., Cheliout-Heraut, F., Bouskraoui, M., Lemione, M., Lacert, P., & Dalattre, J. (1998). Sleep EEG and developmental dysphasia. *Developmental Medicine and Child Neurology, 40*, 595-599.

Plaisted, K. (2001). Reduced generalisation in Autism: an alternative to weak central coherence. In '*The Development of Autism: Perspectives from Theory and Research*', (pp 149-169) J. A. Burack, T. Charman, N. Yirmiya, & P. R. Zelazo (Eds). Lawrence Erlbaum Associates, Inc, Publishers.

Psychology Software Tools, Inc. [E-Prime 2.0]. (2012). Retrieved from http://www.pstnet.com.

Robertson, E. K., Joanisse, M. F., Desroches, A. S., & Ng, S. (2009). Categorical speech perception deficits distinguish language and reading impairments in children. *Developmental Science, 12* (5), 753-767.

Schwab, E. C., Nusbaum, H. C. & Pisoni, D. B. (1985). Some effects of training on the perception of synthetic speech. *Human Factors*, 27, 395–408.

Semel, E., & Wiig, E. (2006). *Clinical Evaluation of Language Fundamentals, 4th Edition*

(CELF-4). Pearson: London, UK.

Stackhouse, J. and Wells, B. (1997). *Children's Speech and Literacy Difficulties: A psycholinguistic framework.* London: Whurr.

Staresina, B.P., Bergmann, T. O., Bonnefond, M., van der Meij, R., Jensen, O., Deuker, L., Elger, C. E., Axmacher, N., & Fell, J. (2015). Hierarchical nesting of slow oscillations, spindles and ripples in the human hippocampus during sleep. *Nature Neuroscience, 18* (11), 1679-1686.

Stark, R. E., & Heinz, J. M. (1996). Perception of stop consonants in children with expressive and receptive-expressive language impairments. *Journal of Speech and Hearing Research, 39* (4), 676-686.

Stewart, M. E., Petrou, A. M., & Ota, M. (2018). Categorical speech perception in adults with autism spectrum conditions. *Journal of Autism and Developmental Disorders, 48*(1), 72-82.

Tamaki, M., Watanabe, T., & Sasaki, Y. (2017). REM sleep stabilizes visual perceptual learning which was rendered fragile by NREM sleep. *Sleep*, 40 (1): A85

Tamminen, J., Payne, J. D., Stickgold, R., Wamsley, E. J., & Gaskell, G. (2010). Sleep spindle activity is associated with the integration of new memories and existing knowledge. *Journal of Neuroscience, 30* (43), 14356- 14360.

Tessier, S., Lambert, A., Chicoine, M., Scherzer, P., Soulières, I., & Godbout, R. (2015). Intelligence measures and stage 2 sleep in typically developing and autistic children. *International Journal of Psychophysiology, 97* (1), 58-65.

Trotti, L. (2017). Waking up is the hardest thing I do all day: Sleep inertia and sleep drunkedness. *Sleep Medicine Reviews, 35*: 76-84.

Tsanas, A., & Gifford, G. D. (2015). Stage-independent, single lead EEG sleep spindle detection using the continuous wavelet transform and local weighted smoothing. *Frontiers in Human Neuroscience, 8* (9), 181.

UCLA: Statistical Consulting Group. from https://stats.idre.ucla.edu/sas/modules/sas-learning-moduleintroduction-to-the-features-of-sas/

Vanderwalle, E., Boets, B., Ghesquie, P., & Zink, I. (2012). Auditory processing and speech perception in children with specific language impairment: Relations with oral language and literacy skills. *Research in Developmental Disabilities, 33*, 635–644.

Vitevitch, M. S., & Luce, P. A. (2004). A web-based interface to calculate phonotactic probability for words and nonwords in English. *Behaviour Research Methods, Instruments, & Computers, 36* (3), 481-487.

Wagner, R., Torgesen, J., Rashotte, C. A., & Pearson, N. A. (2013). *Comprehensive test of phonological processing, 2nd Edition* (CTOPP2). Oxford: Pearson.

Wang, X., Wang, S., Fan, Y., Huang, D. & Zhang, Y. (2017). Speech-specific categorical perception deficit in autism: an event-related potential study of lexical tone processing in Mandarin-speaking children. *Scientific Reports, 7*, article number 43254

Wei, Y., Krishnan, G. P., Komarov, M., & Bazhenov, M. (2018). Differential roles of sleep spindles and slow oscillations in memory consolidation. *PLoS Computational Biology, 14*(7): e1006322. https://doi.org/10.1371/journal.pcbi.1006322

Werchen, D. M., & Gomez, R. L. (2013). Generalizing memories over time: Sleep and reinforcement facilitate transitive inference. *Neurobiology of Learning and Memory,* *100,* 70–76.

Wilhelm, I., Rose, M., Imhof, K. I., Rasch, B., Büchel, C., & Born, J. (2013). The sleeping child outplays the adult's capacity to convert implicit into explicit knowledge. *Nature Neuroscience, 16*, 391-393.

Diekelmann, S., & Born, J. (2008). Sleep in children improves memory performance on declarative but not procedural tasks. *Learning and Memory, 15*:373–377.

Whitteman, M. J., Bardhan, N. P., Weber, A., & McQueen, J. (2015). Automaticity and stability of adaptation to a foreign accented speaker. *Language and Speech, 58* (2), 168-189.

Williams, D., Botting, N., & Boucher, J. (2008). Language in autism and specific language impairment: where are the links? *Psychological Bulletin, 134* (6), 944-963.

Wickham, H. (2016). *ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag New York.

Xie, X., Earle, S., & Myers, E. B. (2018). Sleep facilitates generalisation of accent adaptation to a new talker. *Language, Cognition and Neuroscience, 33* (2), 196-210.

Xie, X., Earle, S., & Myers, E. B. (2016). Sleep talker generalization of accent adaptation. *The Journal of the Acoustical Society of America, 140* (4), 3342-3342.

Ziegler, J. C., Pech-Georgel, C., George, F., Alario, F-X., & Lorenzi, C. (2005). Deficits in speech perception predict language learning impairment. *PNAS, 102* (39), 14110-14115.

Ziegler, J. C., Pech-Georgel, C., George, F., Alario, F-X., & Lorenzi, C. (2011). Noise on, voicing off: Speech perception deficits in children with specific language impairment. *Journal of Experimental Child Psychology 110*, 362–372.

Figure legends

Figure 1. a) Distribution of scores on the Children's Communication Checklist-2; the box indicates scores considered to fall in the range of ASD, cases are marked by group and whether the child has a diagnosis of ASD within the High AI group. b) Distribution of GARS-3 scores showing the split between High and Low AI groups; Low AI (n = 47) mean = 51.2, High AI (n = 30) mean = 96.1.

Figure 2. Example trials for 'biscuit' and 'parrot', synthesised speech is shown in italics.

Figure 3. Training model. a) Performance pre and post training at Session1; post-training only Novel items are included, error bars show standard error. b) Relationship between the Language Composite measure and average performance over Session1. One participant was removed from this analysis after being identified as influential case with DFBETAS- they are shown in red but excluded from the figure summary statistics.

Figure 4. Time-course model. Performance 0 (Day1:AM), 12(pm1) and 24(Day2:AM) hours after, error bars show standard error. Two participants were removed from this analysis after being identified as influential cases with DFBETAS- they are shown in red but excluded from the figure summary statistics.

Figure 5. Interaction shown in the Time-course model between Language Composite, AI Group and Condition. Data points shown as triangles were excluded from the model on the grounds of being overly influential according to DFBETAS; these participants are not included in the figure summary statistics.

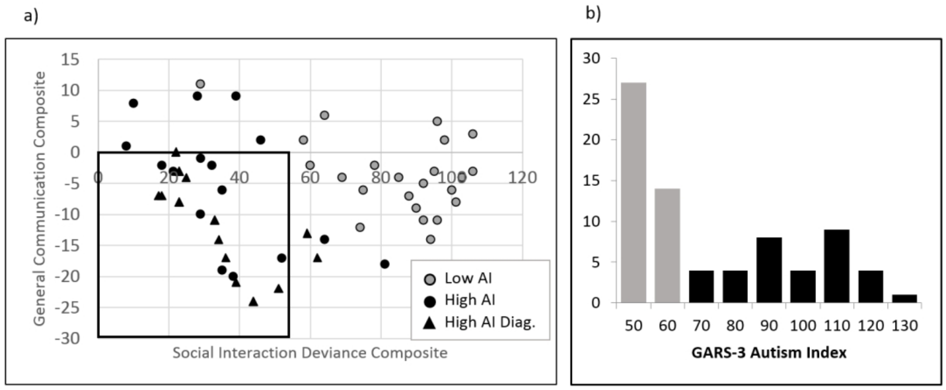
Figure 6. Relationship between REM theta power and overnight change in performance on the Novel condition.

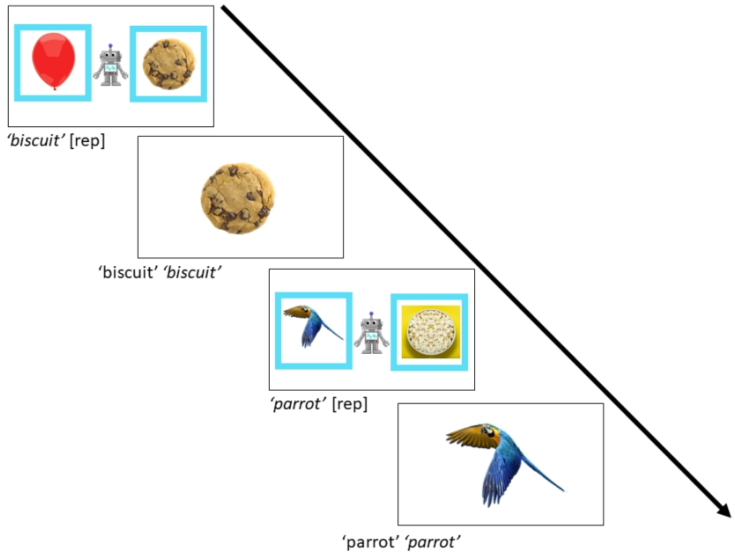
Legends for Figures submitted in Supplementary Materials

SM1: Interaction shown in the Follow-up model between Language Composite, AI Group and Condition. Data points shown as triangles were excluded from the model on the grounds of being overly influential according to DFBETAS; these participants are not included in the figure summary statistics.

SM2: Performance pre and post training at the Day1:AM session (Training model); summary statistics shown for all participants (error bars give standard error), while individual points are only shown for those participants in the High AI group with no diagnosis or pending diagnosis of ASD.

SM3: Performance at sessions Day1:AM-post, Day1:PM and Day2:AM (TimeCourse model); summary statistics shown for all participants (error bars give standard error), while individual points are only shown for those participants in the High AI group with no diagnosis or pending diagnosis of ASD.


a)
b)
General Communication Composite
Social Interaction Deviance Composite
Low AI
High AI
High AI Diag.
GARS-3 Autism Index



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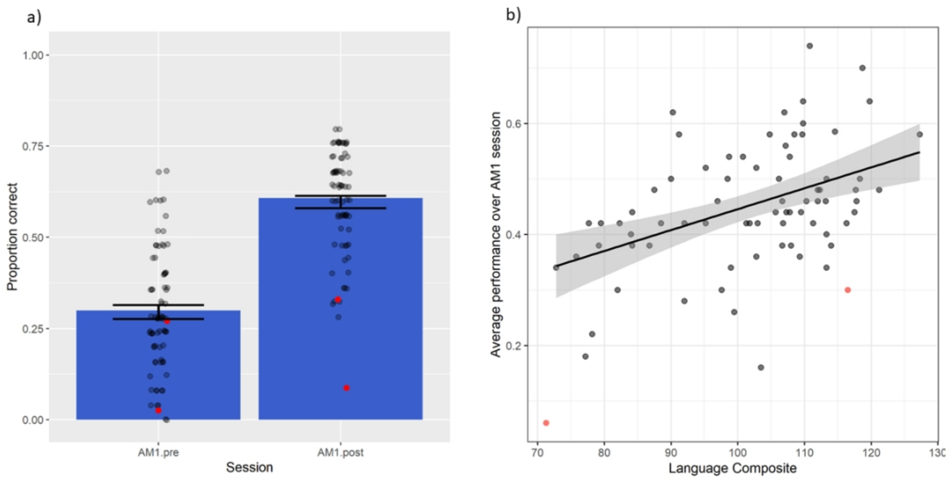
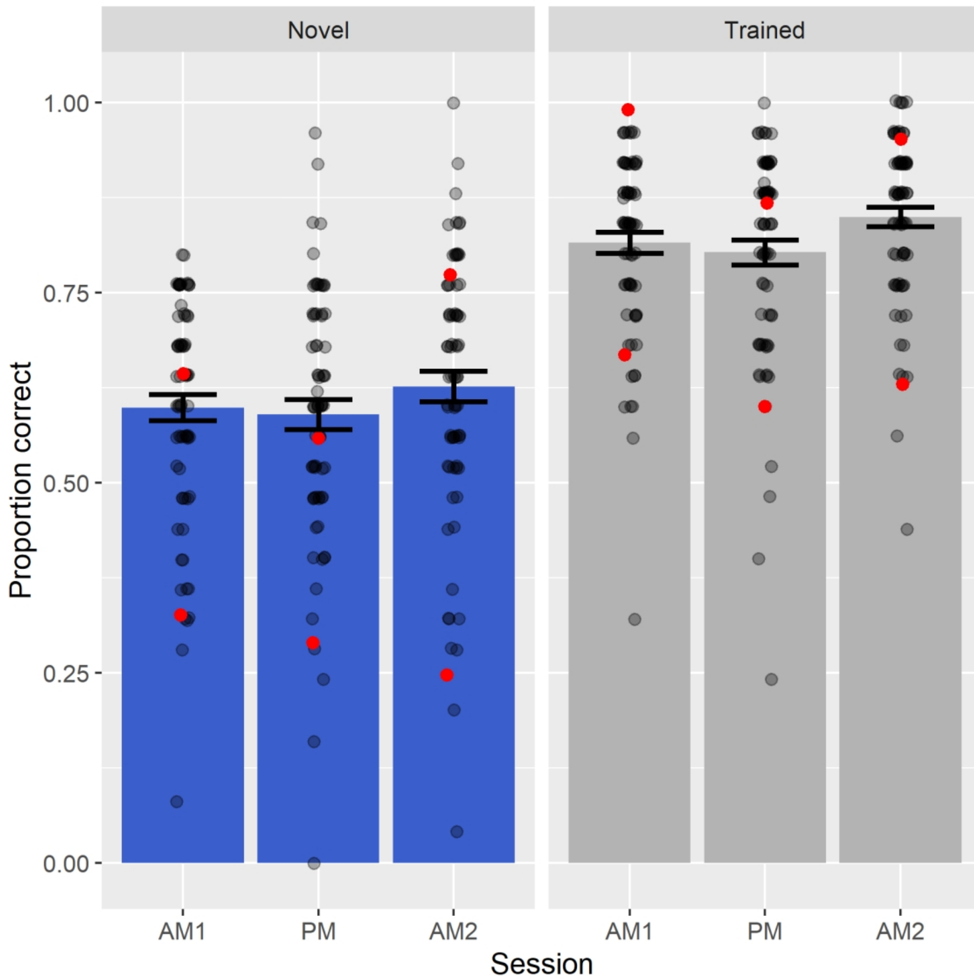

a)
1.00
0.75
0.50
0.25
0.00
Proportion correct
AM1.pre
AM1.post
Session
b)
0.6
0.4
0.2
Average performance over AM1 session
70
80
90
100
110
120
130
Language Composite

3


Novel
Trained
1.00
0.75
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Proportion correct
AM1
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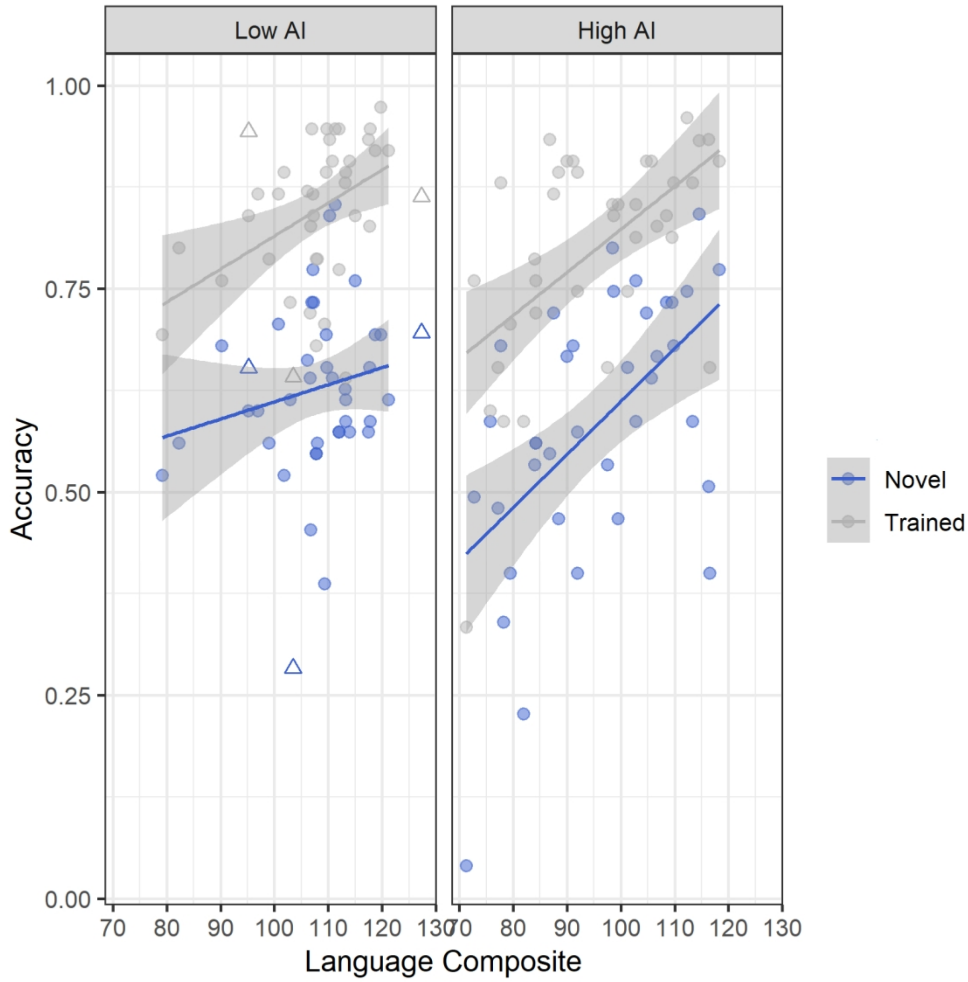
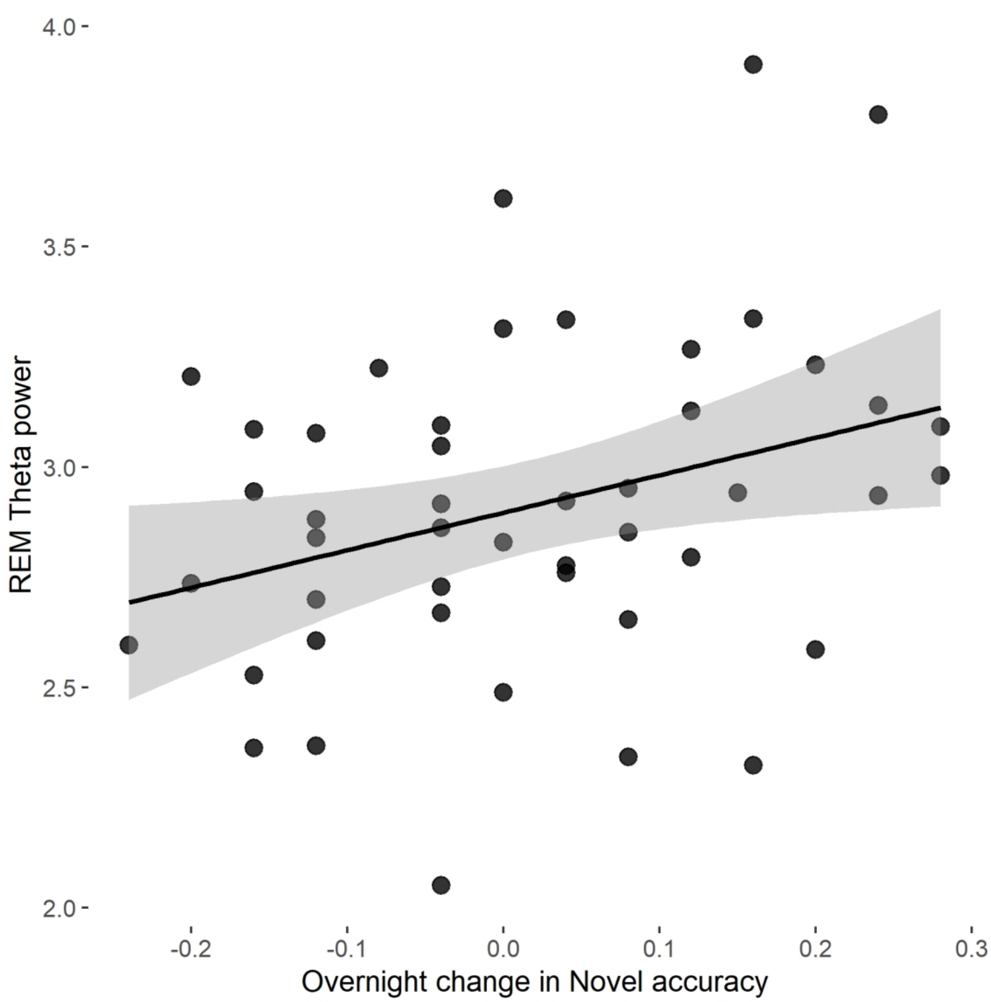
Session



Low AI
High AI
Accuracy
1.00
0.75
0.50
0.25
0.00
70
80
90
100
110
120
130
Language Composite
Novel
Trained


4.0
3.5
3.0
2.5
2.0
REM Theta power
-0.2
-0.1
0.0
0.1
0.2
0.3
Overnight change in Novel accuracy

Group	BPVS	Recall. Sen.	Word Defs.	Elision	NWR	RAN digits	Lang Comp	Matrices	Back digit
Low AI	106.6	108.0	106.8	104.8	110.4	102.4	106.4	100.8	105.8
High AI	95.4	93.4	96.5	95.4	96.9	91.9	94.6	95.3	98.5
t-value	*2.710***	*3.055***	*2.483**	*2.486**	*3.545****	*3.524****	*4.133****	*1.213*	*1.492*
Total	102.3	102.4	102.9	101.5	105.6	98.7	101.8	98.7	103.1

Table 1. Descriptive statistics for cognitive measures, split by AI Group, with group differences shown. *BPVS* = British Picture Vocabulary Scale; *Recall Sen* = Recalling Sentences subtest from the CELF 4; *Word Defs* = Word Definitions subtest from the BAS3; *Elision, NWR & RAN digits* = Elision, non-word repetition and RAN digits subscales from CTOPP2; *Lang Comp* = Language Composite measure; *Matrices* = matrices from BAS3; *Back digit* = backward digit span from BAS3. *$p < .05$, ** $p < .01$, *** $p < .001$.

LIST	%correct@ pilot	Freq.	AoA	Phon. count	Phon p.	Biphone p.	Concrete.
1	54.4	28.31	5.08	5.2	1.23	1.01	4.8
2	55.6	29.69	5.19	4.9	1.22	1.02	4.8
3	55.6	22.56	5.45	5.2	1.25	1.02	4.8
4	57.8	33.39	5.44	5.1	1.26	1.02	4.8
5	58.6	19.24	5.42	5.2	1.24	1.02	4.8
6	54.8	16.09	4.94	5.4	1.25	1.02	4.8
7	54.4	21.31	5.21	5.2	1.24	1.01	4.8
8	54.8	34.40	4.74	5.4	1.24	1.01	4.8
9	56.0	18.74	5.10	5.4	1.27	1.02	4.7
Av.	**55.8**	**24.9**	**5.2**	**5.2**	**1.24**	**1.02**	**4.8**

Table 2. Characteristics of trial items across lists. *%correct@pilot* = percentage of items correctly identified by a pilot sample of ten adults; *Freq*. = frequency of occurrence per million using the SUBTLEX-US frequency norms of Brysbaert & New, 2009; *AoA* = Age of acquisition from Kuperman et al., 2012; *Phon.count* = number of phonemes; *Phon p* and *Biphone p* give average phonotactic probabilities for phonemes and biphones within the words, using an online calculator by Vitevitch, and Luce (2004); *Concrete* = concreteness ratings from Brysbaert, Warriner & Kuperman, (2014).

		Group	Pre	AM1	PM	AM2
Phonological learning: proportion correct	Novel	Low AI	.331 (.172)	.618 (.119)	.596 (.131)	.642 (.165)
		High AI	.251 (.151)	.574 (.173)	.569 (.205)	.609 (.193)
		Total	*.291 (.166)*	*.596 (.149)*	*.583 (.170)*	*.626 (.179)*
	Trained	Low AI	--	.824 (.104)	.832 (.105)	.863 (.094)
		High AI	--	.805 (.133)	.766 (.166)	.826 (.124)
		Total	--	*.815 (.119)*	*.797 (.142)*	*.845 (.111)*
PVT	1/RT	Low AI	--	2.90 (0.40)	2.75 (0.41)	2.80 (0.51)
		High AI	--	2.74 (0.55)	2.61 (0.47)	2.55 (0.55)
		Total	--	*2.85 (0.45)*	*2.70 (0.43)*	*2.72 (0.53)*
	Lapses	Low AI	--	11.09 (11.97)	16.94 (12.95)	16.44 (16.56)
		High AI	--	18.03 (20.00)	23.5 (16.71)	27.90 (20.02)
		Total	--	*13.79 (15.84)*	*19.46 (14.76)*	*20.75 (18.67)*

Table 3. Accuracy means (and standard deviations) for all participants by Session, Condition and Group for the phonological learning task and reciprocally transformed reaction times and lapses for the psychomotor vigilance task (PVT).

	Fixed effects					Random effects	
	b	**SE**	**95% CI**		***z***	***Item***	***Participant***
			Lower	***Upper***		**SD**	**SD**
(Intercept)	**-0.253**	**0.119**	-0.486	-0.020	**-2.123***	1.647	0.240
Session (Pre-Post)	**1.888**	**0.151**	1.592	2.184	**12.495*****	0.355	0.620
Group (Low-High AI)	-0.064	0.161	-0.380	0.252	-0.398	-	-
Language (composite)	**0.277**	**0.0839**	0.113	0.441	**3.299****	-	-
Session*Group	0.254	0.281	-0.297	0.805	0.905	-	-
Session*Language	-0.086	0.147	-0.374	0.202	-0.584	-	-
AI group*Language	0.122	0.169	-0.209	0.453	0.723	-	-
Session*Group*Language	0.234	0.298	-0.350	0.818	0.784	-	-

Table 4. Fixed and random effects for model of performance accuracy Pre and Post training in Session 1: Training model. Model formed from 3726 observations: 75 participants across 225 items and 2 sessions. *Significant at $p < .05$; **Significant at $p < .01$; ***Significant at $p < .001$.

	Fixed effects					Random effects	
	B	SE	*95% CI*		*z*	*Item*	*Participant*
			Lower	*Upper*		SD	SD
(Intercept)	**1.597**	**0.138**	**1.327**	**1.868**	**11.573*****	1.471	0.657
Session1 (AM1-post – PM)	0.067	0.063	-0.057	0.191	1.056	-	-
Session2 (PM – AM2)	**-0.300**	**0.064**	**-0.424**	**-0.175**	**-4.706*****	-	-
Condition (Novel – Trained)	**1.737**	**0.118**	**1.505**	**1.968**	**14.713*****	0.9587	0.405
Group (Low-High AI)	0.166	0.187	-0.200	0.532	0.891	-	-
Language (composite)	**0.468**	**0.101**	**0.269**	**0.666**	**4.625*****	0.211	-
Condition*Group	0.275	0.192	-0.101	0.651	1.433	1.018	-
Condition*Language	**0.281**	**0.092**	**0.101**	**0.460**	**3.066****	-	-
Group*Language	0.165	0.203	-0.233	0.563	0.811	0.451	-
Condition*Group*Language	**-0.409**	**0.185**	**-0.771**	**-0.047**	**-2.216***	-	-

Table 5. Fixed and random effects for model of performance accuracy at the AM1-post, PM and AM2 session: Time-course model. Model formed from 11015 observations: 74 participants across 225 items and 3 sessions. *Significant at $p < 0.05$; **Significant at $p < .01$; ***Significant at $p < .001$.

	Fixed effects					Random effects	
	95% CI					*Item*	*Participant*
	B	**SE**	***Lower***	***Upper***	***z***	**SD**	**SD**
(Intercept)	**1.694**	**0.151**	**1.398**	**1.990**	**11.249*****	1.354	0.573
Condition (Novel – Trained)	**1.671**	**0.179**	**1.320**	**2.022**	**9.351*****	0.918	-
Group (Low-High AI)	0.064	0.210	-0.348	0.476	0.303	-	-
Language (composite)	**0.476**	**0.111**	**0.258**	**0.694**	**4.284*****	-	-
Group*Condition	-0.036	0.256	-0.538	0.466	-0.140	-	-
Language*Condition	0.199	0.133	-0.062	0.460	1.492	-	-
Group*Language	0.047	0.224	-0.392	0.486	0.211	-	-
Condition*Group*Language	**0.555**	**0.276**	**0.014**	**1.096**	**2.012***	-	-

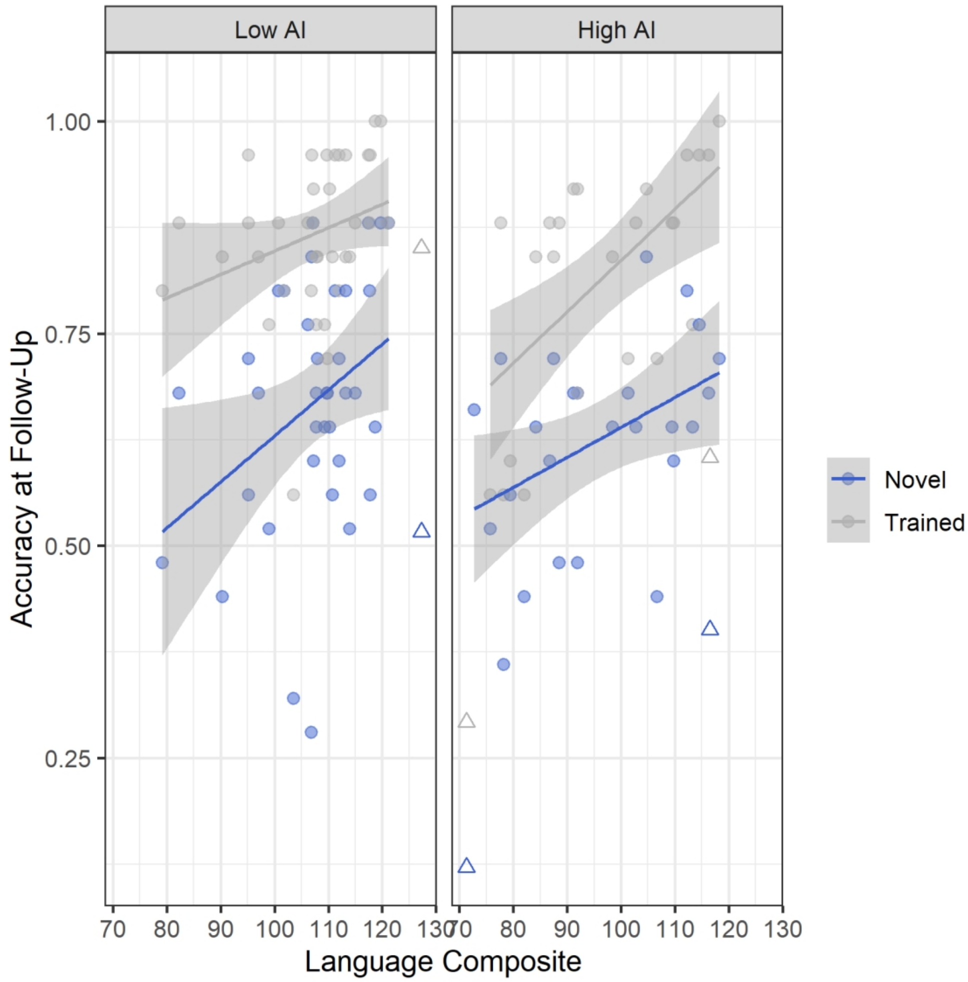
Table 6. Fixed and random effects for model of performance accuracy at Session 3 and the Follow-up session ~four weeks later: Follow-up Model. Model formed from 3050 observations: 61 participants across 225 items. *Significant at $p < .05$; ***Significant at $p < .001$.

Group	Central spindle density		Frontal slow spindle power		Central fast spindle power		Frontal delta power	Central theta power
	Stage2	**Stage 3**	**Stage2**	**Stage 3**	**Stage2**	**Stage 3**	**Stage 3**	**REM**
Low AI	7.59 (2.59)	1.46 (0.92)	2.51 (0.51)	2.203 (0.50)	1.57 (0.49)	1.21 (0.36)	7.74 (0.31)	2.98 (0.42)
High AI	7.66 (3.61)	1.25 (1.40)	2.36 (0.61)	2.219 (0.64)	1.33 (0.58)	1.05 (0.44)	7.64 (0.46)	2.85 (0.37)
t-value	-0.072	0.557	0.900	-0.091	1.458	1.319	0.761	1.185
All pts.	7.61 (2.95)	1.38 (1.11)	2.46 (0.55)	2.210 (0.55)	1.48 (0.53)	1.15 (0.39)	7.70 (0.37)	2.94 (0.41)

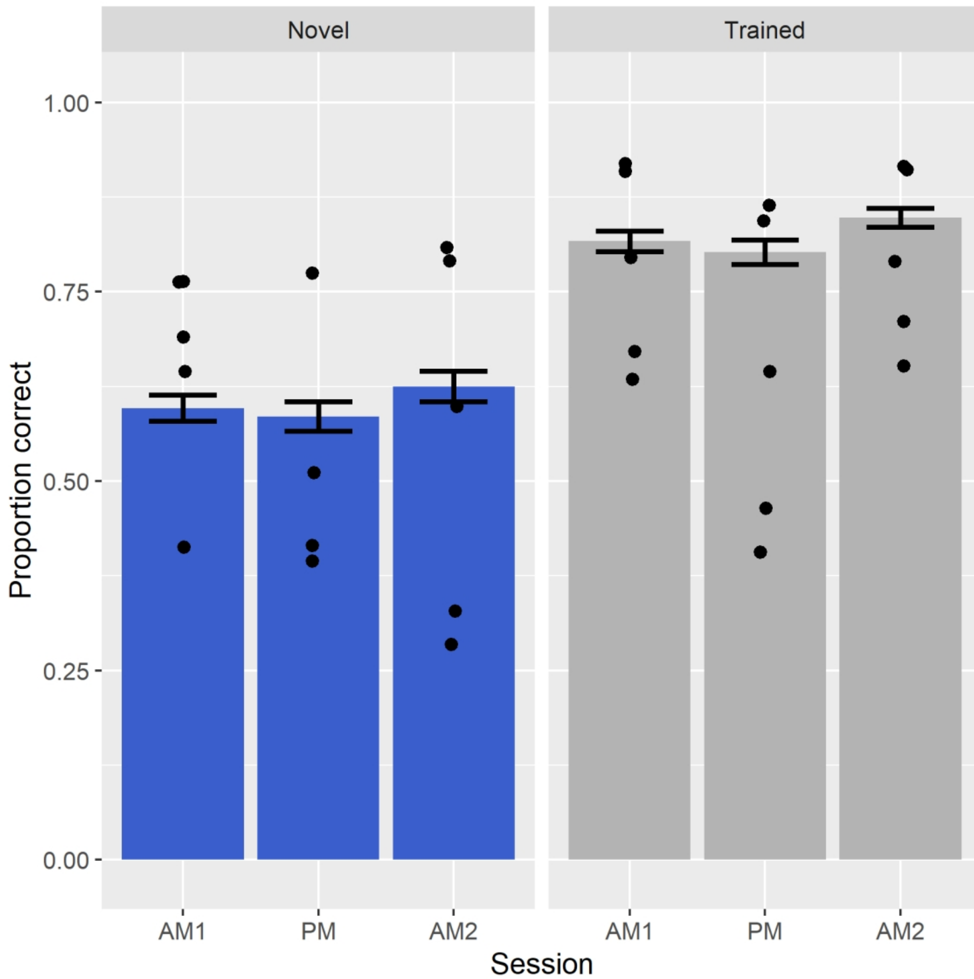
Table 7. Means (and standard deviations) for the sleep parameters used to predict change in overnight performance, presented by group.

		B	SE	Lower 95%CI	Upper 95%CI	t
Novel	Intercept	-0.682	0.504	-1.670	0.307	-1.352
	Age (in months)	-0.002	0.001	-0.005	0.000	-1.880
	Language (composite)					
	Group (Low-High AI)					
	S2 central spindle density	0.009	0.011	-0.013	0.031	0.776
	S2 frontal slow spindle power	-0.071	0.065	-0.197	0.056	-1.094
	S2 central fast spindle power					
	S3 central spindle density	0.047	0.029	-0.010	0.104	1.629
	S3 frontal slow spindle power	-0.092	0.061	-0.211	0.027	-1.508
	S3 central fast spindle power					
	S3 frontal delta power	0.093	0.067	-0.038	0.224	1.389
	REM central theta power	0.173	0.057	0.061	0.285	3.040**
Trained	Intercept	0.212	0.0791	0.057	0.367	2.680*
	Age (in months)					
	Language (composite)	-0.001	0.001	-0.003	0.001	-2.069*
	Group (Low-High AI)					
	S2 central spindle density					
	S2 frontal slow spindle power					
	S2 central fast spindle power	-0.027	0.022	-0.070	0.016	-1.226
	S3 central spindle density					
	S3 frontal slow spindle power					
	S3 central fast spindle power					
	S3 frontal delta power					
	REM central theta power					

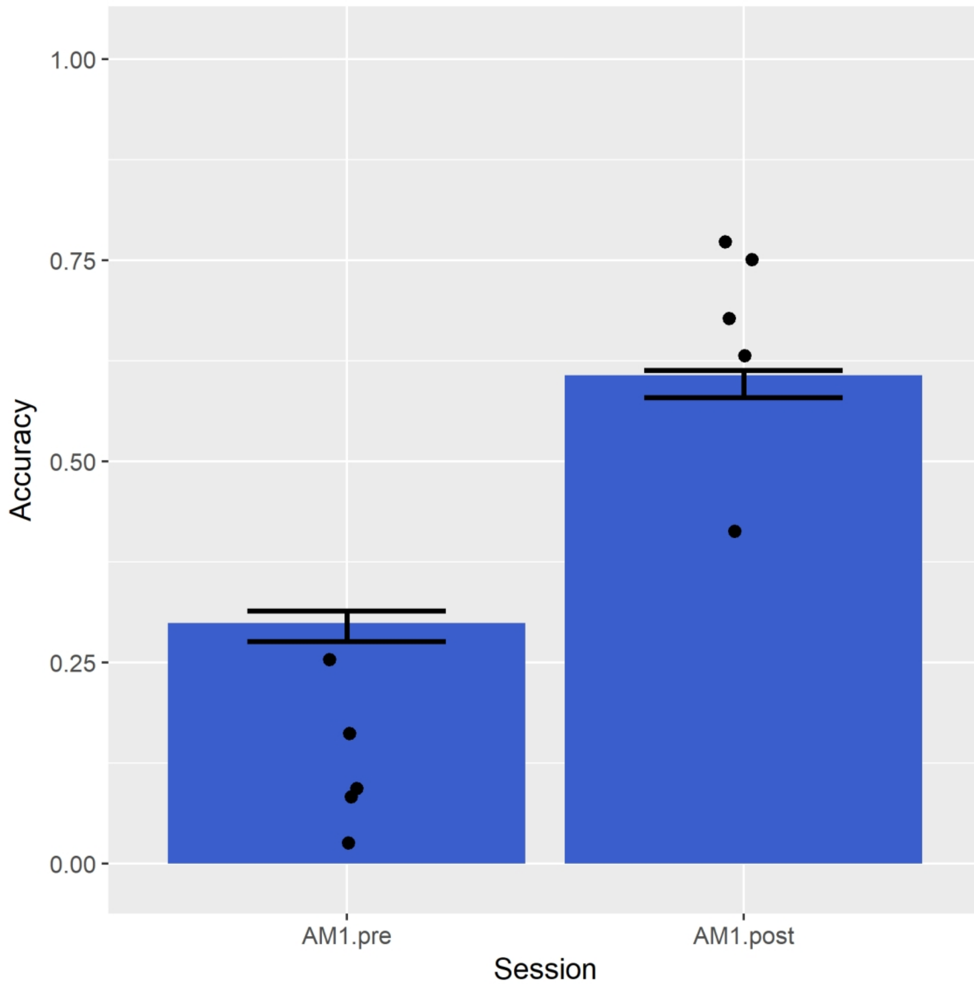
Table 8. Regression model describing relationship between change in performance on the Novel and Trained conditions overnight and sleep parameters. Values are provided for any variables included in the regression model having run leaps subset selection with all eight predictors; cells have been greyed out where a variable was excluded by the leaps package on account of not contributing explanatory power to the best fitting regression model.*Significant at p < .05; **Significant at p < .01.


Low AI
High AI
Accuracy at Follow-Up
1.00
0.75
0.50
0.25
70 80 90 100 110 120 130
Language Composite
Novel
Trained

S1


Novel
Trained
1.00
0.75
0.50
0.25
0.00
Proportion correct
AM1
PM
AM2
AM1
PM
AM2
Session

S2



S3

APPENDIX A: Word lists

	Target	Distractor		Target	Distractor		Target	Distractor
1	hat	hand	**4**	clock	crown	**7**	violin	vegetable
	boots	bee		grapes	gold		bath	bag
	watch	wasp		owl	oar		tree	tie
	axe	arch		ghost	globe		shirt	skis
	gate	glove		slide	square		seal	scarf
	skirt	sun		dice	drum		stick	sword
	shelf	shorts		broomstick	butter		donut	dollshouse
	shoe	ship		baby	bubble		pizza	puddle
	dancer	dolphin		suitcase	seesaw		bottle	blanket
	planet	puppy		dragon	doctor		ketchup	kitten
	towel	tongue		biscuit	balloon		salad	slipper
	noodles	nuggets		blindfold	boxer		garlic	grapefruit
	teacher	teacup		cherry	chicken		raincoat	rhino
	backpack	birdhouse		tiger	toilet		parrot	popcorn
	treasure	toothbrush		toaster	toothpaste		pebble	penguin
	swimsuit	sweatshirt		ladder	lemon		glasses	guitar
	shampoo	shower		cabbage	candle		perfume	pumpkin
	policeman	ponytail		garage	goldfish		atlas	armour
	dustbin	doorbell		sailor	sandbox		circle	celery
	peanuts	pushchair		cave	comb		blackboard	beanbag
	magician	marshmallow		cereal	submarine		scorpion	sharpener
	aeroplane	ambulance		bicycle	buffalo		radio	recorder
	sunglasses	screwdriver		apricot	astronaut		ladybird	letterbox
	tomato	triangle		dinosaur	dalmatian		sunflower	spiderweb
	fireworks	flowerpot		television	toiletpaper		bellybutton	binoculars
2	teeth	toast	**5**	cow	can	**8**	wheelbarrow	watermelon
	bread	bus		duck	doll		house	heart
	tent	truck		shell	shed		train	toad
	door	dress		mouse	moon		spoon	swan
	sea	smile		phone	fist		orange	otter
	witch	wheel		kite	king		spider	sofa
	goat	glass		hedgehog	hotdog		diver	diamond
	flag	fish		crayon	camera		jelly	giant
	sponge	straw		tractor	trainers		puzzle	pasta
	jewel	jeans		beetle	bacon		fireman	fishbowl
	lion	letter		milkshake	melon		clover	cushion
	wallet	walrus		dentist	doughnut		curtain	cowboy
	seahorse	snowflake		earthworm	eagle		teapot	toolbox
	circus	spaceship		elbow	eyebrow		purple	paper
	breakfast	beehive		artist	anchor		plaster	puppet
	apple	ankle		turtle	turkey		pencil	pirate
	window	waffle		taxi	tissue		icecream	iron
	staircase	sparkler		carrot	cupcake		beachball	baboon
	starfish	strawberry		radish	robot		hairbrush	highchair
	burglar	bookcase		paintbrush	peacock		flower	fairy
	photograph	firetruck		mushroom	mermaid		library	licorice
	storybook	skeleton		flamingo	family		spaghetti	cinema
	telescope	trampoline		dragonfly	dandelion		chocolate	chimney
	motorbike	magazine		jellyfish	gingerbread		pineapple	pajamas
	peach	pig		alien	alarmclock		sandcastle	centipede
3	sink	saw	**6**	kiss	key	**9**	castle	canoe
	leaf	lime		whale	wand		ant	arm
	crab	cake		soap	sock		plate	pond

fox	fork	pear	plug	bucket	beaver
desk	dummy	snail	snake	fossil	footprint
shark	shield	sheep	star	rainbow	racket
sweets	swings	crisps	car	lipstick	lizard
princess	poodle	mountain	monster	lunchbox	lightbulb
trophy	trumpet	laces	lorry	helmet	hammer
pillow	pancake	flipflops	finger	sandwich	sausage
petal	panda	snowball	scissors	angel	acorn
daisy	donkey	pretzel	playground	rattle	record
badger	bagpipe	lettuce	lightning	skateboard	snowman
rocket	rubber	moustache	mattress	rabbit	robin
arrow	apron	football	feather	necklace	needle
table	teabag	bathroom	brownie	cartoon	camel
tadpole	teepee	yoyo	yoghurt	present	pocket
lighthouse	leopard	zebra	zipper	giraffe	gokart
horseshoe	hamster	jacket	juggler	rose	rat
bracelet	bandage	scarecrow	sandals	dishwasher	domino
hamburger	hospital	blueberry	basketball	waterfall	wheelchair
rockingchair	rectangle	banana	bulldozer	crocodile	cucumber
barbeque	butterfly	lemonade	lollipop	caterpillar	cauliflower
bear	bat	elephant	eskimo	cat	clown
triceratops	tarantula	raspberry	rollerskate	chips	chess