FILOMENA INÁCIO

# IMPLICIT LEARNING MECHANISMS AND THEIR APPLICATION TO DYSLEXIA

**UNIVERSIDADE DO ALGARVE**

FACULDADE DE CIÊNCIAS HUMANAS E SOCIAIS

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# IMPLICIT LEARNING MECHANISMS
# AND THEIR APPLICATION TO DYSLEXIA

DOUTORAMENTO EM PSICOLOGIA

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**Declaração de autoria de trabalho**

*Declaro ser a autora deste trabalho, que é original e inédito. Autores e trabalhos consultados estão devidamente citados no texto e constam da listagem de referências incluída.*

**Filomena Inácio**

*Aos meus filhos, Madalena e Afonso.*

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# RESUMO


Uma característica inerente ao ser humano é a sua capacidade para adquirir competências ou conhecimentos sem intenção de o fazer, resultando essa aprendizagem da mera exposição às regularidades do ambiente que nos circunda. Este tipo de aquisição designa-se por aprendizagem implícita e o seu exemplo mais marcante é talvez a aquisição da linguagem. Nesta tese procurámos investigar os mecanismos de aprendizagem implícita em duas vertentes. Por um lado, estudámos a deteção da aprendizagem implícita através do rastreamento de movimentos oculares; por outro, procurámos investigar a associação entre a aprendizagem implícita e as competências relacionadas com a literacia, tanto em leitores típicos como em leitores com dificuldades de leitura (dislexia de desenvolvimento).

O estudo da aprendizagem implícita é complexo, pois é difícil aceder ao que efetivamente foi aprendido sem que, ao fazê-lo, haja interferência explícita. No entanto, alguns paradigmas experimentais foram desenvolvidos para aceder a este tipo de aprendizagem com um mínimo de interferência da aprendizagem explícita. Em comum têm o facto de serem constituídos por uma fase de familiarização ou exposição e uma fase de teste ou classificação. Na fase de familiarização, os participantes têm de realizar uma tarefa (por exemplo, uma tarefa de memória, de cópia ou de simples visualização de estímulos) em que são incidentalmente expostos a determinadas regularidades sem terem consciência das mesmas. O objetivo, nesta fase, é que os participantes apreendam implicitamente as regularidades dos estímulos apresentados. Posteriormente, na fase de classificação ou teste, é-lhes pedido para distinguirem, de uma maneira intuitiva, estímulos que apresentam as regularidades a que foram expostos de outros estímulos semelhantes, mas que não possuem essas regularidades. Considera-se existir aprendizagem implícita quando o desempenho dos participantes é significativamente superior ao que seria esperado apenas pela sorte (acima de 50% de acertos) e não há conhecimento explícito desta aprendizagem (isto é, os participantes não conseguem relatar o que os levou a distinguir os estímulos e o conhecimento que possuem é insuficiente para explicar o seu desempenho). A natureza da informação

extraída em tarefas de aprendizagem implícita pode variar, observando-se aprendizagens ao nível da abstração de regras, da representação de fragmentos dos exemplares a que o participante foi exposto, ao nível dos próprios exemplares ou ainda ao nível da sua distribuição probabilística.

Uma das críticas mais frequentemente apontadas a este tipo de tarefas é a necessidade de, imediatamente antes da fase de classificação, revelar aos participantes a existência de regras ou regularidades nos estímulos apresentados. O conhecimento da existência destas regras pode levar à interferência de processos explícitos no desempenho durante a fase de classificação, retirando o caráter puramente implícito da tarefa. Adicionalmente, verifica-se uma dificuldade acrescida na aplicação destes paradigmas em crianças pequenas, pois não há um entendimento claro das instruções em idades mais jovens. Coloca-se então a necessidade de avaliar a existência de aprendizagem implícita através de métodos indiretos.

O primeiro estudo desta tese pretendeu investigar se medidas derivadas do rastreamento dos movimentos oculares podem ser úteis na deteção de aprendizagem implícita, num paradigma de aprendizagem de uma gramática artificial. Neste paradigma, os participantes são expostos a sequências de estímulos (por exemplo, consoantes) cuja composição obedece a um conjunto complexo de regras. Posteriormente é-lhes pedido que classifiquem novas sequências, umas gramaticais (que obedecem às regras da gramática a que foram expostos anteriormente) e outras não-gramaticais (que violam a gramática em apenas uma posição não-terminal da sequência). O objetivo deste primeiro estudo foi explorar a sensibilidade dos movimentos oculares (por exemplo, número e duração das fixações) às violações gramaticais. Numa primeira experiência, registaram-se os movimentos oculares dos participantes enquanto executavam a tarefa clássica de classificação de sequências gramaticais e não-gramaticais (teste ativo). Na segunda experiência, registaram-se também os mesmos movimentos oculares, mas sem a presença de uma tarefa ativa de classificação, tendo os participantes apenas de observar ambos os tipos de sequências (teste passivo). Verificou-se que o padrão de movimentos oculares diferia perante sequências gramaticais e não-gramaticais, tanto em testes passivos como ativos (embora nestes últimos o efeito seja maior). Os resultados demonstram assim que é possível avaliar indiretamente a aprendizagem implícita de uma gramática artificial através do registo de movimentos oculares, um método com claras vantagens pois não exige que haja a revelação da existência de regras, diminuindo o risco de interferência explícita na testagem. Este procedimento pode ser especialmente adequado para avaliar aprendizagem implícita em crianças mais novas, pois não implica a compreensão exigida pelas instruções complexas da fase de classificação.

No segundo estudo da tese, investigou-se a relação entre a aprendizagem implícita e competências ligadas à literacia. Neste estudo, os participantes desempenharam uma série de tarefas destinadas a avaliar a aprendizagem implícita, as competências e hábitos de leitura e o conhecimento ortográfico implícito. Nas provas de conhecimento ortográfico implícito, os participantes deveriam optar entre duas formas alternativas de representar ortograficamente o mesmo fonema, uma delas marcadamente mais frequente na ortografia do Português Europeu (por exemplo, após o ditongo [a:ɪ] o fonema [ʃ] é escrito mais frequentemente com <x> do que com <ch>). Verificou-se que, tanto na prova de escrita por ditado, como na prova de escolha forçada, os participantes optam pelo padrão que é mais frequente e fazem-no de modo implícito, pois esta assimetria não é ensinada formalmente durante a aquisição da leitura e escrita e os participantes não souberam relatar o que os levou a escolher um padrão ortográfico em detrimento do outro. A correlação significativa entre a capacidade de aprendizagem implícita dos participantes e o seu desempenho nas provas de leitura e de conhecimento ortográfico implícito reforça a sugestão de que mecanismos implícitos podem facilitar a extração das regularidades presentes na ortografia e na leitura, contribuindo assim para uma maior proficiência ao nível da leitura e escrita. Por último, verificou-se também que a aprendizagem implícita modera a influência da exposição à ortografia nas competências de leitura, potenciando esta relação. Todos estes resultados levam-nos a sugerir que a aprendizagem implícita tem um papel determinante na aquisição de competências de leitura e escrita e que indivíduos com melhores capacidades de aprendizagem implícita beneficiam mais da exposição à ortografia.

O terceiro estudo pretendeu explorar se uma dificuldade ao nível da aprendizagem implícita poderia contribuir para os défices de leitura apresentados por

crianças disléxicas. Os estudos prévios sobre esta temática apresentam resultados contraditórios que poderão dever-se à heterogeneidade, tanto ao nível das tarefas utilizadas na avaliação da aprendizagem implícita, como ao nível dos critérios de inclusão dos participantes com dislexia. Um dos fatores que contribui para esta disparidade de resultados parece ser o tempo de exposição durante a fase de familiarização, sugerindo que os disléxicos poderão beneficiar de uma exposição mais prolongada. Assim, desenhou-se uma tarefa de aprendizagem implícita com um período mais longo de exposição às regularidades da gramática artificial, estendendo a fase de familiarização por três dias consecutivos. Recorrendo a esta tarefa, comparou-se o desempenho de um grupo de crianças disléxicas que frequentavam o 1º ciclo de escolaridade com o desempenho de dois grupos de controlo: um emparelhado por idade e o outro por nível de leitura. Os participantes disléxicos apresentaram níveis de aprendizagem implícita semelhantes aos observados nos grupos de controlo. Estes resultados sugerem que crianças disléxicas não apresentam défice ao nível da aprendizagem implícita e que esta capacidade preservada pode ser explorada em programas de intervenção na dislexia.

Em suma, os estudos apresentados nesta tese apresentam evidências de que: 1) a aprendizagem implícita pode ser avaliada com interferência mínima de processos explícitos, recorrendo à análise dos movimentos oculares; 2) a aprendizagem implícita tem um papel relevante na extração de regularidades ortográficas, estando relacionada com as competências de leitura e escrita; e 3) as crianças disléxicas não apresentam défices na aprendizagem implícita quando lhes é apresentada uma tarefa que potencie a extração de regularidades, sugerindo que as dificuldades de leitura destas crianças não podem ser explicadas por mecanismos de aprendizagem implícita ineficientes.

**Palavras-chave:** aprendizagem implícita; aprendizagem de uma gramática artificial; aprendizagem estatística; registo de movimentos oculares; leitura; conhecimento ortográfico implícito; dislexia

## ABSTRACT

In this thesis, we conducted three studies to shed light on implicit learning mechanisms and their association with reading and writing processes, both in typical readers and in readers with dyslexia.

In the first study, we explored whether the outcomes of implicit structural sequence learning could be captured in eye movement responses. We tested for sensitivity effects (increased eye movements on a printed violation in an implicit artificial grammar learning task) in two experiments that manipulated the presence of a concurrent behavioural classification test. Results show different eye movement patterns when participants discriminate grammatical and non-grammatical sequences in passive viewing of sequences and that this effect is boosted when participants perform a concomitant classification task. This study shows that implicit acquired knowledge can be detected through the analysis of eye-movement patterns, enabling the study of implicit learning without explicit processing interference.

In study two, we investigated the influence of implicit learning in the literacy skills of adult typical readers. Three main results prompt us to conclude that implicit learning contributes to reading and writing proficiency: 1) in implicit orthographic knowledge tasks where the frequency of orthographic patterns is manipulated, participants tend to choose the most frequent pattern; 2) reading proficiency and the implicit orthographic knowledge decision task were related to an implicit learning task; and 3) implicit learning increases the impact of exposure to print on reading fluency. Altogether, these results suggest a role of implicit learning capacity in the extraction the written language regularities and in the improvement of literacy skills.

In study three, we tested whether dyslexic children present an implicit learning deficit that could contribute to their reading disability. An implicit artificial grammar learning task designed to optimize exposure to regularities was presented to dyslexic children and to two control groups matched by age and reading level. Results showed that dyslexics' implicit learning abilities are at same level as both control groups,

suggesting that the characteristic reading difficulties presented by dyslexics cannot be explained by implicit learning deficits.

In conclusion, the studies presented in this thesis provide evidence that: 1) implicit learning can be tested with minimal interference of explicit processes by measuring eye movement sensitivity patterns; 2) implicit learning intervenes in the extraction of written regularities, contributing to literacy proficiency; and 3) dyslexic children do not present an implicit learning deficit and thus can benefit from this preserved ability to improve their reading skills.

**Key words:** implicit learning; artificial grammar learning; statistical learning; eye-tracking; reading; implicit orthographic knowledge; dyslexia

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# LIST OF ABBREVIATIONS

**ACS –** Associative Chunk Strength

**AGL –** Artificial Grammar Learning

**Gram –** grammatical status

**G/NG –** Grammatical/Non-grammatical item

**H/L –** High/Low Associative Chunk Strength item

**HG/LG –** High/Low Associative Chunk Strength grammatical item

**HNG/LNG –** High/Low Associative Chunk Strength non-grammatical item

**SRT** – Serial Reaction Time Task

# CHAPTER ONE

# GENERAL INTRODUCTION

## IMPLICIT LEARNING MECHANISMS

Every person has experienced learning outside of any form of planned instruction (either academic, parental or self-motivated) and, more generally, without intention to acquire this information about the surrounding world. This kind of learning can be found, for example, in domains as diverse as first and second language acquisition, sensitivity to musical structure, acquisition of knowledge about the physical world and various social skills. This type of learning was named implicit learning by Reber in 1967. In his seminal work, Reber (1967) observed that subjects presented a sensitivity to the statistical properties of the environment without using explicit or verbalizable strategies and that this phenomena should be present in language learning. Although it is well established that there is learning occurring without a conscious effort to learn (the most striking example being learning and using language), some implicit learning mechanisms and their influence on cognitive processes are not fully understood, and therefore they are the scope of this dissertation.

### WHAT IS IMPLICIT LEARNING?

Implicit learning is the non-declarative learning of complex information in an incidental manner, without awareness of what has been learned (Reber, 1967; Seger, 1994). This type of learning occurs by constant exposure to environmental regularities, in an automatic and unintentional fashion, without explicit verbalizable knowledge of what was acquired – in contrast to explicit learning (Kaufman, Deyoung, et al., 2010). Implicit learning differs from explicit learning in its inaccessibility (i.e. subjects typically cannot provide a sufficient or, in many cases, any explicit account of what they have learned), robustness (in the face of time, lack of attentional resources and psychological disorders) and intentionality (tends to be associated with incidental rather than with intentional learning conditions) (Dienes & Berry, 1997). These differences also support the notion that implicit learning depends on cognitive mechanisms separate from those used in inducing explicit knowledge (Seger, 1994).

Several studies have demonstrated that implicit learning is an evolutionarily early process (Marcus, 1999; Saffran, Aslin, & Newport, 1996), independent of age and developmental level (Karatekin, Marcus, & White, 2007; Meulemans, Van der Linden, & Perruchet, 1998; Vinter & Detable, 2003), that it presents an IQ independence (Allen & Reber, 1980; Don, Schellenberg, Reber, DiGirolamo, & Wang, 2003; Reber, 1992) and that it does not decline with age (Cherry & Stadler, 1995; Simon, Howard, Howard, & Al, 2010). Furthermore, and as aforementioned, it does not even decline after occurrence of a brain lesion (Meulemans & Van Der Linden, 2003; Shanks, Channon, Wilkinson, & Curran, 2006) or in the presence of a psychiatric or neurological disorder (Eldridge, Masterman, & Knowlton, 2002; Schwartz, Howard, Howard, Hovaguimian, & Deutsch, 2003), in which cases subjects still retain implicit learning. Implicit learning has even been observed in non-human primates (Hauser, Newport, & Aslin, 2001), indicating that this kind of learning has been in place for a long time, from an evolutionary perspective.

## BRAIN REGIONS ASSOCIATED WITH IMPLICIT LEARNING

Implicit learning involves activity in multiple brain regions. In general, studies suggest that distinct networks might be involved depending on whether subjects are aware of the material they learn. Learning seems to directly produce changes in the brain regions involved in performance, and evidence suggests that additional regions are involved when subjects report awareness (Cleeremans, Destrebecqz, & Boyer, 1998). In the literature, the brain regions most related to implicit learning are the basal ganglia, the association cortex and the frontal cortex. The basal ganglia appears to be involved in aspects of response programming, the association regions appear to be involved in perceptual aspects of implicit learning and the frontal lobes appear to be involved in the evaluation of implicit knowledge in making fluency judgments (Forkstam, Hagoort, Fernandez, Ingvar, & Petersson, 2006; Forkstam & Petersson, 2005; Seger, 1994). Moreover, some studies have suggested that the medial temporal lobe memory system, including the hippocampus, may be involved in implicit learning (Schendan, Searl, Melrose, & Stern, 2003; David R. Shanks et al., 2006). However, the role of the medial temporal lobe memory system remains unclear, as amnesic patients with medial temporal lobe lesions are still capable of implicit learning acquisition, showing that this region has a limited role in several implicit learning tasks (Gagnon, Foster, Turcotte, & Jongenelis, 2004).

## HOW TO STUDY IMPLICIT LEARNING?

The paradigms employed to assess implicit learning typically involve complex, semantically neutral and arbitrary stimulus domains, in order to minimize the influence of the subject's prior knowledge when executing the task. Usually, these implicit learning paradigms consist of two phases: first, there is an exposure to some complex, rule-governed environment under incidental learning conditions, followed by a measure that tracks how well subjects can express their newly acquired knowledge about this environment through performance on the same or on a different task. Most studies also present a measure of the extent to which subjects are conscious of the knowledge they have acquired (Cleeremans et al., 1998).

The paradigms used to study implicit learning can vary in the stimulus structure and the response modality. The most common stimulus types are visual patterns, sequences and functions. Tasks also vary in the different response modalities: conceptual fluency (subjects make ratings or classify items, usually reporting that they rely on their intuition to make such judgments), efficiency (subjects show that they have induced knowledge by their increased speed or accuracy in processing the information) or prediction and control (subjects demonstrate learning by accurately predicting or controlling some aspect of the stimuli) (Forkstam & Petersson, 2005; Seger, 1994). Different paradigms result from a combination of these two properties (stimuli structure and response modality), but the most intensely investigated are the serial reaction time task, the contextual cueing paradigm and the artificial grammar learning paradigm.

The serial reaction time task (SRT - Nissen & Bullemer, 1987) is a visual-motor procedural learning task, i.e., it has a motor component. In this task, usually, participants have to press a button that corresponds to a stimulus light (see Figure 1.1). The light appears in a set sequence of typically 10 positions. Implicit learning is inferred from faster reaction times in responding to reoccurring versus, for example, random sequences, while the participants typically report no or little awareness of re-occurring sequences.

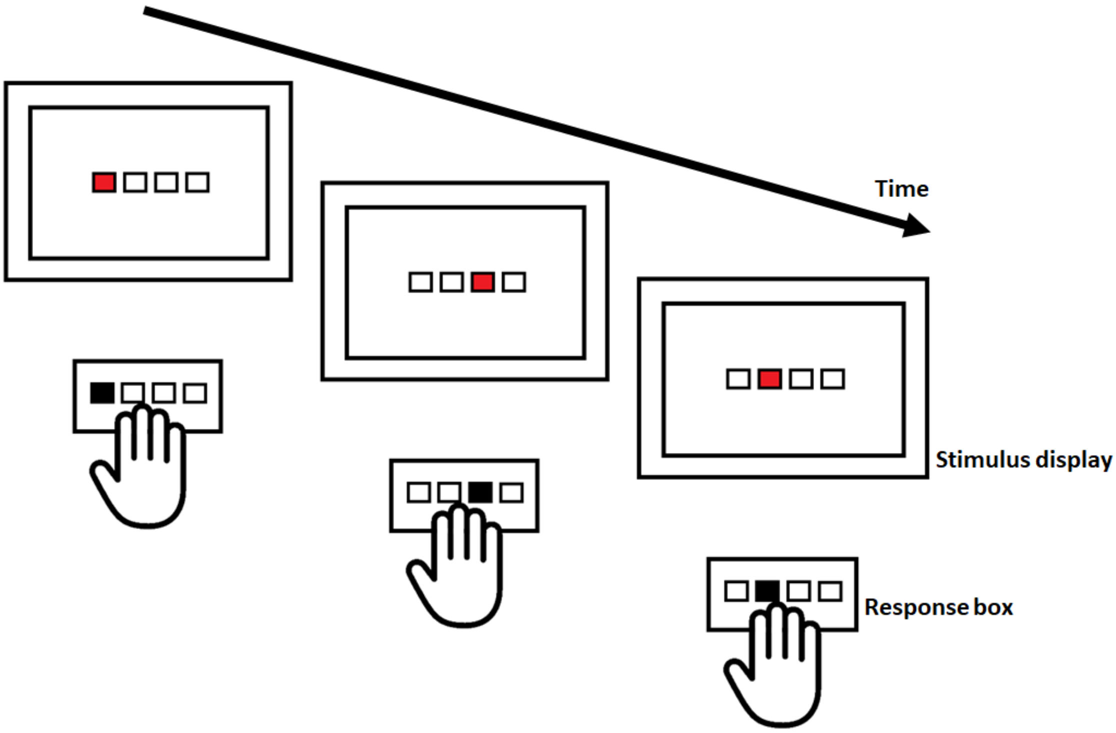


**FIGURE 1.1.** A representation of the serial reaction time task. In these tasks, participants have to press the button that corresponds to a stimulus light as fast as they can. The stimulus presentation corresponds to a fixed sequence, and participants become faster when compared to a random sequence.

In the standard version of the contextual cueing paradigm (see Figure 1.2), participants are instructed to search for a target (e.g., the letter "T") among distractors (e.g., the letter "L") as quickly as possible. Detecting the target becames faster in configurations that are systematically repeated across many blocks of trials compared to when different configurations are presented (Chun & Jiang, 1998; Chun & Jiang, 1999). This learning seems to occur implicitly, as participants do not report remembering such repeated configurations during the visual search. The dominant interpretation of the observed benefit is that learning of associations between spatial configurations and target locations guides attention to the target location (Chun, 2000; Higuchi & Saiki, 2017).

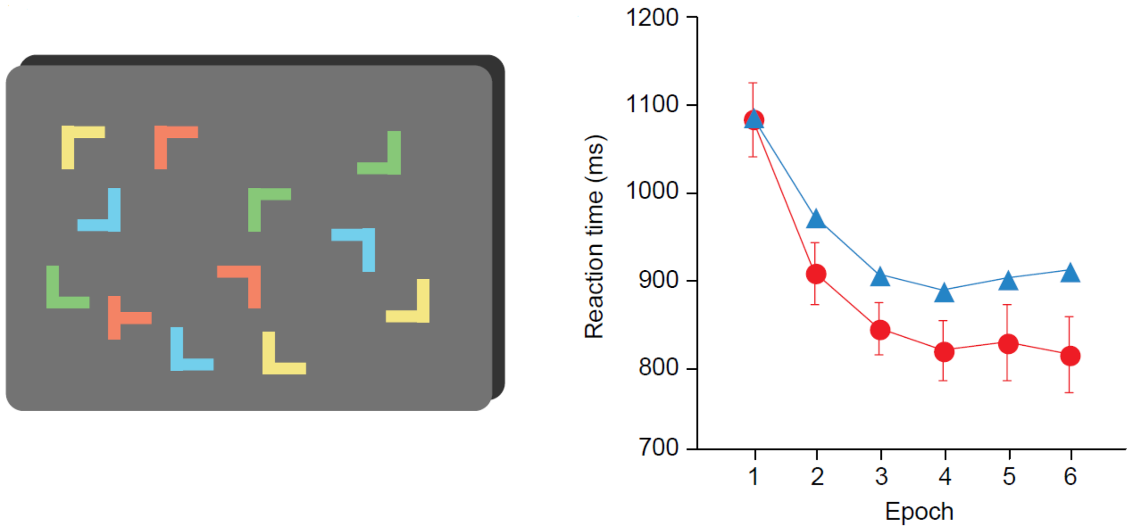


**FIGURE 1.2.** The left panel shows a search display used in contextual cueing experiments, where participants are instructed to search for a T-shaped target among a series of L-shaped distractors. Some search displays are systematically repeated across several blocks of trials, and others are random. The right panel shows the typical result in contextual cuing tasks: participants become faster in identifying the target in repeated trials (red dots) when compared to random trials (blue triangles) (taken from Chun, 2000).

In contrast with the previously described tasks, the artificial grammar learning task (AGL - Reber, 1967) seems to be a more complex implicit learning paradigm that relies on cognitive processes. In the studies that use the artificial grammar learning paradigm, participants are exposed to a sample of grammatical sequences (see Figure 1.3) during the acquisition phase (usually, they are asked to memorize or merely observe the acquisition sequences). It is common to observe that participants become better at memorizing sequences as this acquisition phase progresses, which suggests that the sequence's regularities may be facilitating learning (Reber, 1967). Afterwards, participants are informed that the sequences were generated by a complex set of rules, and new sequences are classified as grammatical or non-grammatical on the basis of the immediate intuition ("guessing"). The typical result observed is that participants perform reliably above the level of chance with little or no explicit knowledge about the rules followed by the stimuli. Participants can also be instructed to classify the new sequences with a preference judgment (like/dislike). In this case, no reference to the underlying grammar is needed, and therefore participants are completely uninformed about the underlying structure of the acquisition material. This classification variant is sensitive to the same knowledge as grammaticality judgments and is related to these judgments (Forkstam, Elwér, Ingvar, & Petersson, 2008).

In order to measure awareness in these implicit learning tasks, researchers frequently use verbal reports (that is, asking participants to describe verbally the structure of the material to which they were exposed), forced-choice tests (e.g. recognition tests or free generation tasks, where it is required that subjects reproduce the sequences they observed, and complete portions of sequences) and subjective tasks (such as confidence ratings, that appear to be unrelated to the performance in the implicit task, or when subjects report guessing, or following their gut feeling, but are performing above chance level). These options, however, are not immune to criticism, as they appear to not be systematic in their measure of awareness (Cleeremans et al., 1998).

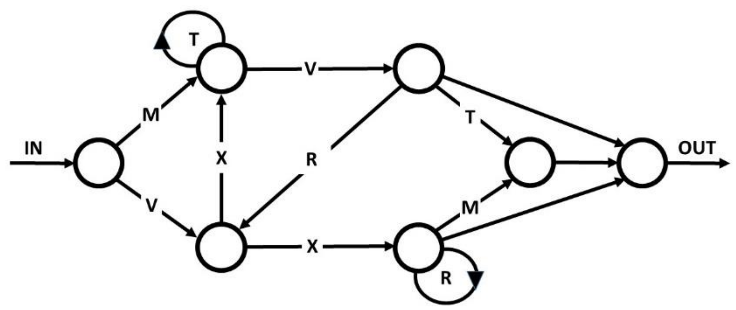


**FIGURE 1.3.** An example of a finite state grammar (adapted from Reber & Allen, 1978) required to generate the sequences presented in artificial grammar learning tasks. Grammatical strings are generated by entering the grammar through the 'in' node and by moving from node to node until the 'out' node is reached. Non-grammatical strings are produced by switching at least one letter to another. An example of a grammatical sequence would be MTTTVRXM, and an example of a non-grammatical sequence would be MTTTVMXM. The sequences can be presented as strings of letters, symbols, colour patches and tones, amongst others.

WHAT IS THE KNOWLEDGE ACQUIRED?

In artificial grammar learning, one of the main topics of discussion concerns what is acquired by the participants. In the earlier years of the implicit learning study, it was assumed that learning was unconscious and abstract (Reber, 1967). These claims generated controversy, and several studies provided evidence that there are different types of information extracted in implicit learning tasks (see Figure 1.4), including exemplar-specific knowledge.

According to the abstract view, and in the context of AGL tasks, where participants show better than chance performance on novel letter stings, it is assumed that participants are learning the abstract rules that govern the formation of letter sequences (Allen & Reber, 1980; Reber, 1992). The same argument is used in sequence learning tasks, where it is assumed that the reduced reaction times reflect the abstraction of the rules presented by the stimuli material (Lewicki, Czyzewska, & Hoffman, 1987). This view assumes that the structure of the stimuli and their relationships are abstracted independently of the surface features of the presented material. In fact, there is evidence from the paradigm of transfer in AGL that even if the letters forming the study items are changed in a consistent way for the test of

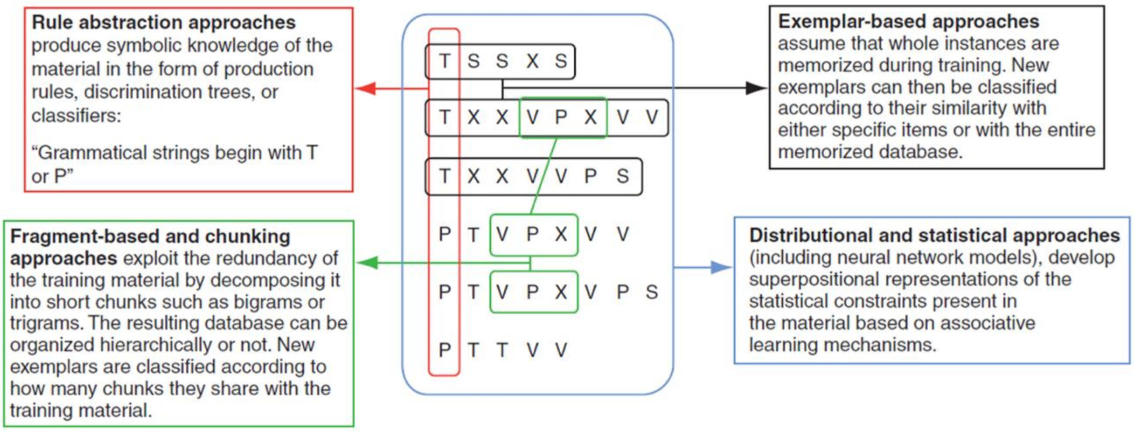


**FIGURE 1.4.** A representation of the knowledge extracted from the AGL task, according to the different described views. Participants that perform above chance in AGL tasks might have learned something about the rules of the grammar from which the strings have been generated (red); they may have memorized frequently occurring fragments or chunks of the strings (green); they may have memorized entire strings from the learning phase (black); or they may have become sensitive to the statistical structure of the entire set of training exemplars (blue) (taken from Cleeremans, 2009).

grammaticality (e.g., S is always replaced by T), participants still outperform chance level (Altmann, Dienes, & Goode, 1995). This transfer phenomena occurs even if one stimulus modality is transferred to another modality (Gomez, 1997). However, a decrease in performance is usually observed (Pacton, Perruchet, Fayol, & Cleeremans, 2001). Furthermore, on one hand, the abstract view is vague and does not specify how the process occurs and what information is stored, and on the other hand, there is evidence that other mechanisms than the abstract ones can account for performance in implicit learning tasks.

Some studies suggested that participants were gaining knowledge specific to the training exemplars, and this exemplar-specific knowledge is used to make their judgments (Vokey & Brooks, 1992). The instance-based model suggests that participants store the different exemplars in memory and then judge whether the novel items present a similarity with the stored items to classify them. However, the grammaticality factor also presented a significant and additive effect, that is, the similar non-grammatical items were less classified as grammatical than the similar grammatical items. Furthermore, Vokey and Brooks (1992) suggested that the similarity may also be computed with the whole set of study items instead of a single item. The currently prevalent interpretation keeps the idea of some kind of pooling or summation over multiple episodes, but privileges a formulation in terms of statistical regularities.

While the instance-based model considers whole exemplars, the fragment-based approach considers elementary components (e.g., the individual letters or small groups of letters in the AGL task). It was observed that participants demonstrate sensitivity to chunk strength: the number of times the bi-gram or tri-gram chunks within the item have been repeated across the training set. For each letter sequence, the overall chunk strength can be calculated by averaging the chunk strength of the bi-grams and tri-grams (Meulemans & Linden, 1997). Nevertheless, there is also evidence that significant sensitivity to grammaticality remains even when similarity and fragment overlap is carefully controlled for (e.g. Forkstam, Elwér, Ingvar, & Petersson, 2008). A combination of several learning processes, both rule-based and exemplar-based, seems to take place in implicit learning. Depending on the specific constraints of the tasks, different mechanisms might underlie the performance: either knowledge based on n-grams or knowledge based on abstracting grammatical structure (Meulemans & Linden, 1997).

Several factors might intervene in the outcomes of implicit learning tasks. It has been shown that intention to learn has an influence on the results. Subjects perform better if they are instructed to discover the rules (Ziori & Dienes, 2012), although this advantage disappears if the sequence presented is probabilistic (Jimenez, Mendez, & Cleeremans, 1996). However, this result is not straightforward, since some studies suggest that instructions to learn can also disrupt implicit learning (Fletcher et al., 2005). Furthermore, and despite it has been extensively said that implicit learning involves automatic processes that engage independent systems, a decrease in implicit learning has been observed when attention is not fully available (e.g. Cohen, Ivry, & Keele, 1990). Nevertheless, several studies suggest that implicit learning is relatively robust in the face of distraction and independent of subjects' orientation to learn (see, for a brief review, Cleeremans et al., 1998).

For several years, the focus of the field was to determine whether implicit learning could be entirely isolated from explicit learning. However, it has been observed that there might be different degrees of implicit learning and different kinds of implicit learning, along with relations between them, as well as different degrees of implicit and explicit knowledge interactions.

## STATISTICAL LEARNING

In 1996, Saffran and colleagues presented a pioneer study, where 8-month-old infants, who were briefly exposed to a continuous stream of repeating three-syllable nonsense words, showed sensitivity to the difference between the three-syllable sequences and foil sequences made up of the same syllables recombined in a different order. This study demonstrated that infants are able to use the statistics of the input stream to discover word boundaries in connected speech, a process labelled by the authors as statistical learning (Saffran et al., 1996). Statistical learning is closely related to implicit learning, as both approaches rely on the capacity that humans have to learn without awareness of the products of learning (Perruchet & Pacton, 2006).

In statistical learning experiments (see Figure 1.5), such as in the already described implicit learning experiments, participants are exposed to material that contains a hidden, repetitive structure, and consequently, learning occurs as a consequence of exposure to positive examples (Batterink, Reber, Neville, & Paller, 2015). The difference between the implicit learning and statistical learning approaches emerges in the views of the to-be-learned stimuli. In the former, the influence of multiple past events is based on rules, and in the latter, is based on statistics (specifically, frequency, probability or contingency). No one disputes the existence of statistical learning (in the implicit learning literature, it refers to fragment-based knowledge), but the necessity to extract the rules (in addition to statistical learning) is a more controversial subject. Some authors claim the necessity of this rule-based knowledge, and others claim that the sensitivity to statistical regularities is able to account for performance in most of the experimental situations that were initially devised to provide an existence proof for rule learning, including transfer settings (Perruchet, 2008).

Despite these differences, both statistical learning and implicit learning are thought to be domain-general phenomena, focusing on the learning mechanisms acting on attended information in incidental, unsupervised learning situations. In recent studies, it has been observed that researchers of implicit and statistical learning assume that this kind of learning arises from the same general mechanism, leading to a growing number of cross-references and to the occasional use of the two expressions as synonymous (Batterink et al., 2015; Perruchet & Pacton, 2006).

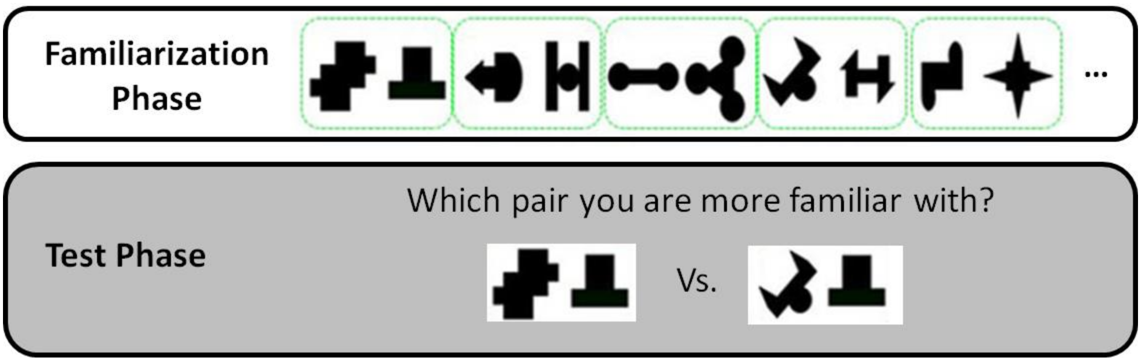


**FIGURE 1.5.** An example of a statistical learning task. In the familiarization phase, participants are exposed to sequences of doubles in a continuous stream, without awareness that a pattern exists. In the test phase, participants are asked which double was previously presented together. Results typically show that participants can distinguish what was the previously presented double above chance (adapted from Bogaerts, Siegelman & Frost, 2016).

## WHAT DO THE EYES TELL US ABOUT IMPLICIT LEARNING?

Eye-tracking measures reflect acquired knowledge when learning is implicit, in contextual cueing tasks. In these tasks, implicit learning of the contextual information (the spatial configuration) facilitates visual search performance throughout an internal "saliency map" for a scene currently in view. Attention and eye movements are deployed to regions of high saliency, facilitating an observer's ability to acquire or react to objects or events within that area of a scene (Chun, 2000; Jiang, Won, & Swallow, 2014). The eye movements appear to be related to the behavioural performance in contextual cueing paradigms: it has been shown that the number of fixations and saccades required to scan a scene before the target is found decreases along with a decrease in search time (Hout & Goldinger, 2012; Li & Tseng, 2004; Manelis, Reder, Manelis, & Reder, 2012; van Asselen, Sampaio, Pina, & Castelo-Branco, 2011). It has also been observed that the anticipation of the spatial position of a target has relied on saccade latency (Amso & Davidow, 2012) and saccade length (Jiang et al., 2014). In SRT tasks (both with and without manual response), it was also observed that anticipatory eye movements reflected sequence learning, thus serving as a direct measure of implicit sequence learning (Marcus, Karatekin, & Markiewicz, 2006; Vakil, Bloch, & Cohen, 2017).

Studies using the eye-tracking methodology with AGL paradigms are scarce and, because there are no spatial targets, different approaches are required. In order to perform in AGL tasks, participants are typically informed that the sequences to which they have been exposed present an underlying grammar. It has been suggested that such a disclosure might lead to explicit processing (Buchner, 1994; Manza & Bornstein, 1995), making it difficult to assess to implicit knowledge. Indirect measures such as preference judgments (like/dislike) have been proposed as a sensitive alternative, with the advantage of providing for a baseline measure (see, for example, Forkstam et al., 2008). However, an involuntary index of learning would be even more akin to the implicit character of the process, and it would facilitate expanding AGL research to populations such as infants and animals.

Only three studies have explored the outcomes of AGL with eye-tracking measures. In the first one, Heaver (2012) measured the size of pupil dilatations when observing grammatical and non-grammatical sequences at the test phase of an AGL task.

She found no difference in the pupillary response to the different sequences, unlike the behavioural response, where participants showed that they were able to distinguish grammatical from non-grammatical sequences. In the testing phase of two studies, Wilson and colleagues (Wilson et al., 2013; Wilson, Smith, & Petkov, 2015) presented to macaques and humans auditory grammatical and non-grammatical sequences through speakers and analysed the time participants gazed at the speaker area as a function of the grammatical status of the sequence. The primates showed longer gaze times for the sequences that violated the grammar (Wilson et al., 2013; Wilson et al., 2015), but this paradigm did not show any effect in humans (Wilson et al., 2015). Nevertheless, in the behavioural task, participants could identify the sequences that violated the artificial grammar relative to those that did not.

Taken together, these results seem to suggest that AGL effects do not show up in eye-tracking measures. However, the paucity of studies and methodologies employed does not allow us to draw definitive conclusions about if and how AGL effects can be measured with the eye-tracking methodologies. For example, these studies did not probe sensitivity effects in visually presented sequences (increased eye movements on the target letter or event, the one violating the grammar), and so the possibility of observing sensitivity effects in implicit AGL remains untested. In this context, we aimed, in the first study of this dissertation, to test for these sensitivity effects in an implicit AGL paradigm and to determine the type of sensitivity effect associated with implicitly acquired knowledge, expecting to find an involuntary index of implicit learning processes measured by AGL tasks.

## THE INFLUENCE OF IMPLICIT LEARNING IN READING AND WRITING PROCESSES

It has been shown that from a very early age, humans can extract the regularities in the surrounding environment, supporting the acquisition and development of different skills, such as language (Kaufman, DeYoung, et al., 2010; Saffran et al., 1996; Saffran, Pollak, Seibel, & Shkolnik, 2007). Languages are a well-structured environment, with strings of words that present statistical correlations and transitional probabilities, constraining them and determining their internal structure (Frost, Siegelman, Narkiss, &

Afek, 2013). Infants acquire these linguistic statistical patterns just from exposure to them, supporting language acquisition (Saffran et al., 1996), and these implicit processes might also occur when children acquire literacy skills. Upon the probabilistic patterns observed in the language, the written patterns of the alphabetic systems that represent these languages are also characterized by a set of correlations that determine the possible co-occurrences of letter sequences that culminate in several orthographic patterns, which can vary in their occurrence (Frost et al., 2013). These probabilistic orthographic patterns are not explicitly taught, but they are known by children even in early stages of reading and writing acquisition, suggesting that implicit learning has a role in literacy skills acquisition (Treiman, 2018).

Learning to read and write requires explicit instruction, and one cannot learn how to read and write just by exposure to print. Despite the different written languages that present several statistical regularities, it seems that implicit processes only operate when they have importance to the learner and capture his or her attention (Treiman, 2018). Nevertheless, this acquisition is an obligatory event in most cultures, and as soon as explicit instruction about how to read and write is given, we observe implicit mechanisms taking place (for a review, see Arciuli, 2018 and Treiman, 2018).

In addition to the probabilistic patterns observed in the written language, each writing system denotes a different level of consistency (i.e., high or low correlations) in the mapping of graphemes to phonemes (Frost et al., 2013). Although these mappings between graphemes and phonemes are explicitly taught, in several languages, particularly in the ones with a deeper orthography, these mappings are not one-to-one, but many-to-many, meaning that one grapheme can correspond to several different graphemes, and one grapheme can correspond to several phonemes. Furthermore, several of these mappings depend upon positional and other contextual regularities, making it difficult to teach them explicitly (Arciuli, 2018).

Although many phonological, orthographic and morphological rules that enable us to read and write correctly are taught explicitly during reading acquisition, the total amount and complexity of the combinations that the written language presents and that are required to become a proficient reader and speller would be overwhelming, and thus statistical learning has to play a role (Steffler, 2001). According to the statistical learning perspective on literacy development, even from an early age, and before formal instruction begins, some properties are acquired in the form of the written words to which children are exposed, such as their own name or the text presented in children's books. It has been shown that these pre-learners use the letters that appear more frequently in the material to which they are exposed more often in their initial spellings (without real correspondence to the phonology) (e.g. Pollo, Kessler, & Treiman, 2009; Treiman, Kessler, Boland, Clocksin, & Chen, 2017). For example, pre-learners of Portuguese present more vowels in their attempts to write words than pre-learners of English, which actually corresponds to the higher proportion of vowels in Portuguese words when compared to English words (Pollo et al., 2009).

Overall, there is evidence that suggests that children must benefit from implicit learning mechanisms to extract the written language regularities in order to become proficient readers and spellers. However, typically, such evidence comes from the use of some of these regularities by children or adults, which are not taught in an explicit manner, and so it is deducted that such knowledge is acquired implicitly. In the second study of this dissertation, we aimed to assess whether implicit statistical learning is related with reading proficiency and implicit orthographic knowledge. Specifically, we first intend to assess if an individual that presents a better performance in a visual statistical learning task also has better skills in using the implicit regularities that exist in the Portuguese written language, but that are not explicitly taught. Secondly, we intend to assess if reading in Portuguese is related to statistical learning, such as in English, an opaque orthography (Arciuli & Simpson, 2012b) or if there is no such relationship, as in Spanish (a more transparent orthography) (Nigro, Jiménez-Fernández, Simpson, & Defior, 2015).

### IMPLICIT LEARNING AND DYSLEXIA

Developmental dyslexia (hereafter, dyslexia) is characterized by severe and persistent difficulties in learning how to read in children and adults who otherwise possess average intelligence and motivation necessary for accurate and fluent reading. It occurs in the absence of other cognitive disabilities and is not due to extraneous factors, such as sensory acuity deficits, socio-economic disadvantage or lack of exposure to high quality literacy instruction (Lyon, Shaywitz, & Shaywitz, 2003; Tunmer & Greaney, 2011; Vellutino, Fletcher, Snowling, & Scanlon, 2004). Dyslexia is probably the most common learning disorder in children and affects approximately 5.4% of Portuguese students from the second to the fourth grade (Vale, Sucena, Viana, & Correia, 2011). The deficits presented by dyslexics typically persist throughout adulthood, even though the individual might develop compensating strategies (Shaywitz & Shaywitz, 2005; Vellutino et al., 2004). Behavioural and brain-based research indicates that the manifestations observed in dyslexia are complex, making it difficult to provide a unitary account of the etiology of this common and heritable learning disability. It seems that there is a consensus, however, that dyslexia is a neuro-developmental disorder with a biological origin, which affects written language and which has a range of clinical manifestations (Frith, 1999).

The most dominant feature associated with dyslexia is the phonological processing difficulty, specifically, underspecified or/and less accessible phonetic representations in dyslexic readers (e.g., Boets et al., 2013; Ramus et al., 2003). In fact, dyslexic individuals seem to perform bellow average in a variety of phonological tasks, including tasks requiring verbal short-term memory (e.g. digit span), phonological awareness (e.g., phoneme deletion and rhyme judgments), phonological decoding (e.g., pseudoword reading) and lexical retrieval (e.g., rapid automatized naming) (Hulme, Snowling, & Carroll, 2005; Ramus et al., 2003; Ramus & Szenkovits, 2008; Shaywitz, 2003; Tijms, 2004; Wagner, Torgesen, & Rashotte, 1994). Additionally, dyslexia has been linked to non-linguistic processing deficits, including visual and auditory processing (Sela, 2014), visual spatial attention (Franceschini, Gori, Ruffino, Pedrolli, & Facoetti, 2012) and, discussed more recently, implicit learning (for a review, see Lum, Ullman, & Conti-Ramsden, 2013; Schmalz, Altoè, & Mulatti, 2016; van Witteloostuijn, Boersma, Wijnen, & Rispens, 2017).

In the last decade, a significant interest in implicit learning in dyslexia culminated in several studies, although the link between reading disabilities and implicit learning is still not well understood. Few explanations, however, of how a weakness in implicit learning of sequential information could account for the phonological processing and reading problems in dyslexia have been proposed. Nicolson and Fawcett (Nicolson & Fawcett, 1999; Nicolson, Fawcett, & Dean, 2001) proposed that the reading problems in dyslexia are linked to problems with learning and/or adapting the phonological knowledge and automatizing skills necessary to support reading. Specifically, the cerebellar deficit hypothesis of dyslexia (Nicolson & Fawcett, 1999; Nicolson et al., 2001) claims that children with dyslexia have unusual difficulty in automatizing any skill, whether motor or cognitive. Because implicit learning has been closely linked with automatic learning mechanisms (Conway & Pisoni, 2008), it may well be that an implicit learning deficit would affect learning of grapheme-phoneme associations in children with dyslexia and eventually prevent them from reaching a high degree of automaticity in reading (Sperling, Lu, & Manis, 2004).

Howard, Howard, Japikse and Eden (2006) also suggest that poor implicit learning could hinder the establishment of adequate phonological processing, as well as learning orthographic-phonological representations. The authors propose that a combination of a phonological deficit with an impaired sequence learning system could manifest as a failure in applying implicit or probabilistic rules required for fluent application of grapheme-phoneme correspondences and, therefore, leading to reading difficulties (see also Sperling et al., 2004).

Implicit learning in dyslexia has typically been studied with the serial reaction time task and the artificial grammar learning task, although with variations in the complexity and length of the stimuli used (in the rare exception, the contextual cueing task was used - see Howard et al., 2006). Many of these studies have reported an implicit learning deficit in dyslexics (Du & Kelly, 2013; Ise, Arnoldi, Bartling, & Schulte-Körne, 2012; Jiménez-Fernández, Vaquero, Jiménez, & Defior, 2010; Kahta & Schiff, 2016; Laasonen et al., 2014; Deny Menghini, Hagberg, Caltagirone, Petrosini, & Vicari, 2006; Pavlidou, Kelly, & Williams, 2010; Pavlidou, Williams, & Kelly, 2009; Stoodley, Harrison, & Stein, 2006; Stoodley, Ray, Jack, & Stein, 2008; Vicari et al., 2005; Vicari, Marotta, Menghini, Molinari, & Petrosini, 2003), but this finding has not always been replicated (Deroost et al., 2010; Gabay, Schiff, & Vakil, 2012; Howard et al., 2006; Kelly, Griffiths, & Frith, 2002; Menghini et al., 2010; Nigro, Jiménez-Fernández, Simpson, & Defior, 2016; Pothos & Kirk, 2004; Rüsseler, Gerth, & Münte, 2006). The variability of these findings prevents any reliable conclusion, and the question of whether implicit learning deficits are indeed found in dyslexia remains unanswered.

Two recent meta-analyses combined the information provided by these studies, one for the SRT task (Lum et al., 2013) and the other for the AGL task (van Witteloostuijn et al., 2017). Both meta-analysis provided evidence supporting the hypothesis that implicit learning is impaired in dyslexia. However, the findings of the AGL meta-analysis might be contaminated by the presence of a publication bias, and thus no solid conclusions can be drawn (van Witteloostuijn et al., 2017). Furthermore, both meta-analytic studies suggest that age has a moderating impact on the difference between participants with and without dyslexia: studies with adult samples showed smaller effect sizes than studies with child participants (Lum et al., 2013; van Witteloostuijn et al., 2017). In addition, Lum and colleagues' (2013) study also found an interaction between age and the amount of exposure to the sequences, showing that differences between groups might be minimal when participants are older and there is more exposure to the sequences.

Taken together, these findings seem to suggest that it is still unclear whether dyslexics present an implicit learning deficit when tested with AGL tasks, whether the development of the implicit learning abilities is delayed in dyslexia and if differences between individuals with dyslexia and individuals in control groups emerge only when participants have a limited opportunity to implicitly learn the sequences. In the third study of this dissertation, we aimed to clarify this issue by comparing the performance of dyslexic children and their typically developed age matched pairs in an AGL task specifically designed to maximize the exposure to sequences. Additionally, we also compare the performance of dyslexic children with a younger control group matched by reading level in order to verify if a given deficit is a consequence of the reduced reading experience or a delay in the implicit learning abilities.

# CHAPTER TWO

## STUDY 1 - Eye Movements in Implicit Artificial Grammar Learning


### ABSTRACT

Artificial grammar learning (AGL) has been probed with forced-choice behavioral tests (active tests). Recent attempts to probe the outcomes of learning (implicitly acquired knowledge) with eye-movement responses (passive tests) have shown null results. However, these latter studies have not tested for sensitivity effects, for example, increased eye movements on a printed violation. In this study, we tested for sensitivity effects in AGL tests with (Experiment 1) and without (Experiment 2) concurrent active tests (preference- and grammaticality classification) in an eye-tracking experiment. Eye movements discriminated between sequence types in passive tests and more so in active tests. The eye-movement profile did not differ between preference and grammaticality classification, and it resembled sensitivity effects commonly observed in natural syntax processing. Our findings show that the outcomes of implicit structured sequence learning can be characterized in eye tracking. More specifically, whole trial measures (dwell time, number of fixations) showed robust AGL effects, whereas first-pass measures (first-fixation duration) did not. Furthermore, our findings strengthen the link between artificial and natural syntax processing, and they shed light on the factors that determine performance differences in preference and grammaticality classification tests.

## INTRODUCTION

The artificial grammar learning (AGL) paradigm probes implicit sequence learning (Forkstam & Petersson, 2005; Reber, 1967; Seger, 1994; Stadler & Frensch, 1998; van den Bos & Poletiek, 2008) and models aspects of the acquisition of structural knowledge such as linguistic syntax (Christiansen, Conway, & Onnis, 2012; Christiansen, Louise Kelly, Shillcock, & Greenfield, 2010; Conway, Karpicke, & Pisoni, 2007; Lelekov-Boissard & Dominey, 2002; Silva, Folia, Hagoort, & Petersson, 2016; Tabullo, Sevilla, Segura, Zanutto, & Wainselboim, 2013; Zimmerer, Cowell, & Varley, 2014). The paradigm involves exposure and test phases. In the *exposure* phase, participants are given positive examples of a grammar, often letter sequences. In implicit versions of AGL, participants are kept unaware that the sequences are constructed according to rules (Figure 2.1) and may thus be referred to as *grammatical* sequences. In the *test* phase, novel grammatical sequences are presented together with sequences containing at least one violation of grammar rules (i.e., *non-grammatical sequences*). Participants are asked to make grammaticality judgments under forced-choice conditions, and any implicitly acquired knowledge is inferred from the accuracy of those judgments—that is, from *behavioral discrimination* between grammatical and non-grammatical sequences.

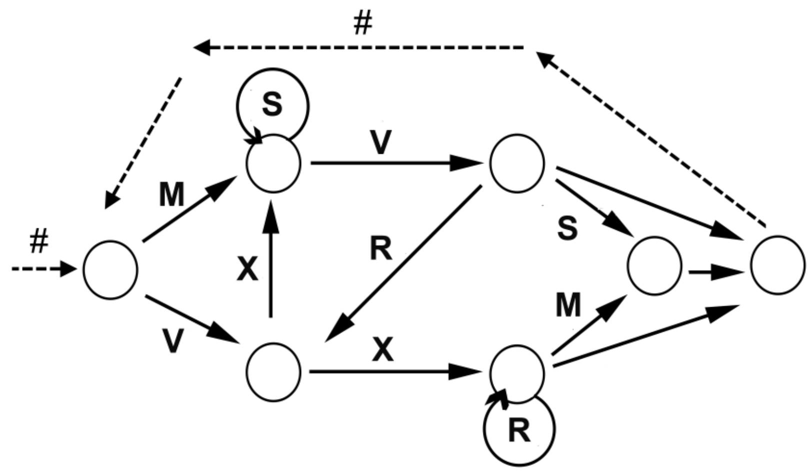


**FIGURE 2.1.** The artificial grammar used in this study. Grammatical sequences are generated by traversing the transition graph along the indicated directions (e.g., MSVRXVS). An example of a non-grammatical counterpart would be MSXRXVS, with X being the violating target letter and V a legal target letter.

The importance of keeping participants unaware of the learning targets has generated some discussion on grammaticality judgment tasks because the test-instructions highlight the existence of rules and might therefore lead to explicit processing (Buchner, 1994; Manza & Bornstein, 1995). Indirect accuracy-free judgments, such as preference classification (like/dislike), have been proposed as an alternative (Forkstam et al., 2008; Gordon & Holyoak, 1983; Manza & Bornstein, 1995), with the advantage of allowing for a baseline (pre-exposure) measure of accuracy underlying a proper-learning design (Petersson, Elfgren, & Ingvar, 1999b, 1999a). Even though preference judgments are sensitive (Folia et al., 2008; Folia & Petersson, 2014; Forkstam et al., 2008; Silva et al., 2016; Uddén, Ingvar, Hagoort, & Petersson, 2012), an involuntary index of learning would be even more akin to the implicit character of the process, and it would afford expanding AGL research to populations such as infants and animals. Eye movements are not always involuntary (Hayhoe & Ballard, 2011), but the probability of being so is high, in the context of viewing AGL test sequences. In addition, eye-tracking measures reflect acquired knowledge when learning is implicit (Giesbrecht, Sy, & Guerin, 2013; Jiang, Won, & Swallow, 2014, but see Coomans, Deroost, Vandenbossche, Van Den Bussche, & Soetens, 2012, for the potential role of covert attention). In this study, we investigate the suitability of eye-tracking measures in characterizing the outcomes of AGL (implicitly acquired knowledge), focusing on the possibility that some form of ocular discrimination of sequence types parallels the behavioral discrimination that is observed in successful implicit AGL.

Eye-tracking measures have been extensively used in spatial implicit learning, where space is the learning target. Paradigms measuring the anticipation of the spatial position of a target have relied on saccade latency (Amso & Davidow, 2012) and saccade length (Jiang et al., 2014). Visual search paradigms relating to contextual cuing effects (implicit learning of spatial context) have measured the number of saccades (Hout & Goldinger, 2012) or fixations (Manelis, & Reder, 2012) required to scan a scene before the target is found. Scan-path measures, defining the exploration overlap of scenes, have been used to index implicit memory (Ryals, Wang, Polnaszek, & Voss, 2015).

In AGL there are no spatial targets and different approaches are required. To our knowledge, only three studies have probed the outcomes of AGL with eye-tracking methodologies. Heaver (2012) tested participants for pupillary responses to grammatical and non-grammatical sequences at the test phase, and found no discrimination of sequence types based on pupil size. Wilson and colleagues (Wilson et al., 2013; Wilson, Smith, & Petkov, 2015) delivered auditory stimuli through speakers and analyzed the time participants gazed at the speaker area as a function of the grammatical status of the sequence. The paradigm worked for primates (Wilson et al., 2013, 2015), who showed longer gaze times for non-grammatical sequences, but it did not show any effects in humans (Wilson et al., 2015). However, a behavioral forced-choice (grammaticality classification) did work in humans, and it was suggested that this might be due to increased levels of attention in the active (forced-choice) compared with the passive (eye-tracking only) task. A slightly different, yet related explanation for why eye-tracking measures alone might fail to capture AG knowledge relates to the processes that may or may not be recruited depending on the behavioral task (e.g., Leeser, Brandl, & Weissglass, 2011). Given that AGL involves syntax-like processing (e.g., Christiansen et al., 2010) - and hence a focus on dependencies between sequence elements—the required type of analysis may not be recruited unless there is an active and suitably syntax-oriented task. The results on implicit AGL with preference classification— apparently a nonsyntax-oriented task—contribute to argue against this possibility (Folia et al., 2008; Folia & Petersson, 2014; Forkstam et al., 2008; Silva et al., 2016; Uddén et al., 2012), but it may nevertheless be considered.

Whether passive tests fail in facilitating attention in general, or in eliciting syntactic analysis in particular, one may expect that the eye-tracking signatures of AGL resemble the so-called *sensitivity effects*. Sensitivity effects have been described in the literature on natural syntax processing, and they refer to the fact that readers fixate longer or regress more frequently from a violating word compared with its syntactically correct counterpart (Godfroid et al., 2015; Keating, 2009; Lim & Christianson, 2014; Sagarra & Ellis, 2013). The reason why sensitivity effects may be expected is not that AGL materials resemble written words: AGL sequences are meaningless and unpronounceable, and they are presented one at a time, so interword regressions do not exist. Instead, sensitivity effects may be expected on the grounds that AGL models the acquisition and the processing of natural syntax (Christiansen et al., 2012, 2010;

Conway et al., 2007; Lelekov-Boissard & Dominey, 2002; Silva et al., 2016; Tabullo et al., 2013; Zimmerer et al., 2014), and so the processing of dependencies among sequence items (letters, in this case) is likely to mirror the processing of dependencies among words (sentence subunits) in natural language. Moreover, sensitivity effects have been obtained in natural language without readers being specifically asked to do syntactic judgments, so it is possible that they emerge in passive eye-tracking tests, when no additional task is requested. However, natural language is different in one fundamental aspect. Unlike AGL stimuli, natural language sentences have both lexical and sentence-level meaning. The presence of semantic content may be sufficient to increase the levels of attention or to drive syntactic analysis. From this viewpoint, it is less certain that sensitivity effects emerge in AGL, which is semantic-free. As already noted above, Wilson and colleagues (2015) suggested that AGL effects do not show up in eye-tracking measures. However, Wilson and colleagues (2015) did not probe sensitivity effects (increased eye movements on the target letter or event, the one violating the grammar) and so the possibility of observing sensitivity effects in implicit AGL remains untested.

The first objective of our study was to test for sensitivity effects in a proper-learning implicit AGL paradigm (pretest-posttest design, with pre-exposure and post-exposure measures of knowledge) with and without a concurrent forced-choice, active test. In the first experiment (see Table 2.1), we used active tests and participants were also tested in a baseline (pre-exposure) preference classification task. We compared this with a final (post-exposure) preference classification as well as with a grammaticality classification test. In Experiment 2, we started with passive tests and added a final active test (grammaticality classification) for within-subject comparisons. We predicted that sensitivity effects would be weaker with passive, eye-tracking only tests (Experiment 2) than with active ones (Experiment 1), and that the introduction of an active test would boost ocular discrimination in Experiment 2. An issue of interest was the comparison between ocular discrimination in final preference versus grammaticality classification in Experiment 1. Several AGL studies have shown quantitative differences in behavioral performance for final preference versus grammaticality classification (Folia et al., 2008; Folia & Petersson, 2014; Forkstam et al., 2008; Silva et al., 2016; Uddén et al., 2012). Behavioral tests completely depend on offline (final) decision processes, which are highly susceptible to the self-monitoring of performance (e.g., 'Should I say I like it?' in preference, vs. 'Should I say it is correct?' in grammaticality). Differences between preference and grammaticality decisions concerning the processes engaged may be responsible for the quantitative differences observed so far in behavioral tests. In contrast, eye-tracking measures are online measures that capture the whole judgment process. This may include final decision processes and influences of self-monitoring, but it also includes the whole processing time before a specific response is planned, making eye-tracking measures less susceptible to decision-related influences than behavioral ones. Thus, if differences between preference and grammaticality classification show up in behavioral tests but not in concurrent eye-tracking measures, this would suggest that final decision processes are critically involved in behavioral differences.

Table 2.1

*Design of the Two Experiments*

| Phase | Day 1 | Day 2 | Day 3 | Day 4 | Day 5 |
|---|---|---|---|---|---|
| Experiment 1 | | | | | |
| Exposure (G) | Yes | Yes | Yes | Yes | Yes |
| Active test (G-NG) | **Baseline preference** | | | | **Final preference** |
| | | | | | **Grammaticality** |
| Experiment 2 | | | | | |
| Exposure (G) | Yes | Yes | Yes | Yes | Yes |
| Passive test (G-NG) | **Passive baseline** | **Passive Test 2** | **Passive Test 3** | **Passive Test 4** | **Passive Test 5** |
| | **Passive Test 1**[a] | | | | |
| Active test (G-NG) | | | | | **Grammaticality** |

*Note.* G and NG refer to sequence types (G = grammatical; NG = non-grammatical). Text in bold indicates eye-tracking recordings.

[a] Passive 1 was run after exposure on Day 1.

The second objective of this study was to determine the type of sensitivity effect associated with implicitly acquired knowledge. Despite claims that there is no one-to-one mapping between eye movements and awareness (Godfroid & Schmidtke, 2013) and that triangulation with verbal data is required to determine whether learning was implicit or not (Godfroid & Winke, 2015), it has been proposed that regressions (movements from right to left) are associated with explicit knowledge (Godfroid et al., 2015). This claim was based on the assumptions that regressions are controlled processes (Reichle, Warren, & McConnell, 2009), and that implicit knowledge is accessed by automatic rather than controlled processing. In our study, we tested for the more general concept of *second-pass reading*, including regressions (right to left movements) as well as progressions (left to right) to the violating (target) letter after the first-fixation on it. For this reason, we used measures related to whole-trial time (dwell time, number of fixations), considering first-pass (first-fixation duration) and second pass measures (dwell-to-first-fixation ratio) separately.

In the two experiments, we controlled for the effects of local subsequence familiarity, measured as associative chunk strength (ACS, Knowlton & Squire, 1996; Meulemans & Linden, 1997), to rule out the possibility that learning is based on overt, surface features of the sequences (D R Shanks & John, 1994) instead of structural features of the underlying grammar (Folia et al., 2008; Folia & Petersson, 2014; Forkstam et al., 2008; Silva et al., 2016; Uddén et al., 2012). As in our previous studies, we used a multiday paradigm to allow abstraction and consolidation processes to take place (e.g., Nieuwenhuis, Folia, Forkstam, Jensen, & Petersson, 2013).

## EXPERIMENT 1: EYE MOVEMENTS IN ACTIVE TESTS

In the first experiment, we tested whether eye movements concurrent with active, forced-choice classification tests reveal artificial grammar learning (AGL). We used a proper-learning paradigm (Folia et al., 2008; Folia & Petersson, 2014; Petersson et al., 1999b, 1999a), where the focus is on changes in discrimination between sequence types (grammatical vs. non-grammatical) after exposure.

### METHOD

#### PARTICIPANTS

Thirty-three healthy adults with normal or corrected-to-normal vision volunteered to take part in the experiment. Due to excessive eye-tracking artifacts, three participants were excluded from further analysis. From the remaining 30 participants, 13 were female (M age ± SD = 26 ± 5). All participants were prescreened for medication use, history of drug abuse, head trauma, neurological or psychiatric illness, and family history of neurological or psychiatric illness. Written informed consent was obtained from all according to the protocol of the Declaration of Helsinki.

### STIMULUS MATERIAL

Sequences were generated from the Reber grammar represented in Figure 2.1 (5 to 12 consonants long, from the alphabet [M, S, V, R, X], see the Appendix 1). For a detailed description of the procedure to generate the stimulus material, see Forkstam, Hagoort, Fernandez, Ingvar, & Petersson, 2006). For the exposure phase (see Table 2.1), we generated one acquisition set with 100 grammatical sequences (G). To engage participants in same/different judgments (cf. Procedure section), we paired 50 of these sequences with themselves ("same") and the remaining 50 with another string from the set ("different"). We created five different pairings for presentation in each of the 5 days of exposure, using the same 50/50 proportion. For the test phase, we generated three additional classification sets, each with 60 novel grammatical (G) and 60 non-grammatical (NG) sequence pairs that were matched for associative chunk strength (ACS). In sum, each classification set consisted of 30 sequences of each sequence type: high ACS grammatical (HG), low ACS grammatical (LG), high ACS non-grammatical (HNG), and low ACS non-grammatical (LNG). HG sequences were paired with HNG, and LG with LNG, such that each pair differed in one letter, named the *target letter* (legal in G vs. violating in NG). The target letter appeared in random, nonterminal positions.

### PROCEDURE

Participants were exposed to implicit acquisition sessions over 5 days (see Table 2.1). The sessions were constructed as short-term memory tasks of visually presented grammatical sequences. Each sequence from the 100-sequence set was presented during 4 s on a computer screen, followed by a fixation cross for 1 s. After the cross, either the same or a different sequence was presented for 4s. The participant responded whether the sequences were either the same or different, in a self-paced manner and without performance feedback. Each session lasted approximately 30 min. In the test sessions, participants performed a forced-choice classification task. On the first day, before the first acquisition session, participants classified 120 sequences according to whether they liked it or not, based on their immediate intuitive impression, or “gut feeling” (i.e., *baseline preference* classification). They did the same with novel sequences on the fifth day, after the last acquisition session (i.e., *final preference* classification). Then we informed participants about the existence of an underlying complex set of rules generating the acquisition sequences, and they performed the third and last classification session. They classified sequences in the new set as grammatical or not (*grammaticality* classification) on the basis of their immediate intuitive impression (“gut feeling”). The three classification sets were disjoint (no overlap) and balanced across participants. Each sequence was presented for four seconds, after which the participant responded with a button press. At the end of the experimental procedure, participants filled in a questionnaire to assess potential explicit knowledge of the grammar. They were asked whether they had noticed any regularity in the stimuli. They were also asked about any technique they might have used for classification, including any combination of letters and/or the location or pattern of letters within the sequences. Finally, they were invited to generate 10 grammatical sequences.

### EYE –TRACKING DATA RECORDING AND PREPROCESSING

Eye movements from test sessions were recorded with an EyeLink 1000 eye-tracking system (http://sr-research.com). Sequences were presented centrally on the computer screen, and they were preceded by fixation crosses aligned with the first (left-most) letter. The monitor, 55.8 cm wide, was placed 70 cm away from the participant. At this distance, each letter (font size 36) encompassed approximately 1° of the horizontal visual angle. Before each classification session, a five-point calibration procedure was implemented, and calibration was repeated after tracking errors larger than 0.5°. Participants placed their head on a chin rest. They were asked to stand still, relax, and blink as little as possible during sequence presentation. The raw signal was inspected, such that participants with high levels of artifacts (blinks and signal loss) were excluded from the analysis (n = 3). The analysis was based on the number and duration of events (fixations and saccades). Each letter sequence and target letter was surrounded by rectangular areas of interest, such that four target-letter-related eye-movement features would be computed: the *dwell-time proportion* (fixation and saccade times on the letter, relative to dwell time on the whole sequence), the *proportion of fixations* (number of fixations on letter relative to those on sequence), the (absolute) *duration of the first-fixation*, and the *ratio between dwell time* on the target letter and the *first-fixation* on it (*dwell/first-fixation*). The first two features provide an overall picture of the processing of the target letter. First-fixation duration indicates the first-pass response to the violation, whereas the ratio between dwell and first-fixation signals the amount of second-pass responses in relation to first-fixation duration, which may vary across participants/trials and thus becomes normalized. We preferred this relative measure of second-pass over an absolute one because it seemed to better capture how much the participant needed to expand her/his first (variable) contact with the target. Data were inspected for outliers (±3 SD > M), and outlier trials were removed from the analysis. Null values for first-fixation duration and dwell-to-first-fixation ratio were classified as missing values (no fixation on the critical letter). The data points that entered the analysis (out of 7200 potential data points—30 participants x 120 items x 2 tests) are quantified in Tables 2.2 and 2.3.

### STATISTICAL ANALYSIS

Behavioral and eye-tracking data were analyzed with linear mixed-effects models as implemented in the lme4 package (Bates, 2010; Bates, Maechler, Bolker, & Walker, 2014) for R (http://www.R-project.org/). We focused on changes in the effects of grammatical status (gram, G vs. NG) and/or ACS (high vs. low) across tests. We compared baseline preference with final preference to check for learning (increased discrimination between G and NG), and then we compared the two active tests (final preference and grammaticality). The primary interaction of interest was Test x Gram, defining grammar-based learning. Conversely, Test x ACS tested for learning based on the knowledge of surface features. The Test x Gram x ACS interaction defined the extent to which grammaticality or ACS effects depended on each other.

The full model had test (baseline preference vs. final preference or final preference vs. grammaticality), grammatical status (gram, G vs. NG), and ACS (high vs.

Low) as fixed factors, together with random intercepts for participants. The model was fitted using the ML criterion so as to allow significance testing, which was achieved by comparing the full model with models without the interactions whose significance was being tested. Namely, we first tested the Test x Gram x ACS interaction by comparing the full model with a second one (Model 2, without the third-order interaction), testing for (Test x Gram) + (Test x ACS). Then we tested Test x Gram and Test x ACS by respectively comparing Model 2 with Model 3a (without Test x Gram), defined by (Test x ACS) + Gram, and Model 2 with Model 3b (without Test x ACS), defined by (Test x Gram) + ACS. Additionally, and given the large sample size, absolute *t* values larger than 2 were taken as indicators that the fixed-effects parameters were significant at the 5% level (Baayen, Davidson, & Bates, 2008). When significant, Test x Gram x ACS interactions were broken down (Test x Gram in high ACS vs. low ACS). For significant Test x Gram interactions, we ran post hoc tests of grammatical status effects on pre-exposure and post-exposure tests separately. Ideally, there should be no pre-exposure grammatical effects (no grammar knowledge), but these do not contradict learning evidence as long as significant Test x Gram interactions exist, and this is why a proper-learning design is important. Concerning post-exposure grammatical effects, these should be observed as evidence that effective sensitivity to grammatical status resulted from exposure.

We used a similar approach to analyze behavioral data. Here, the dependent variable was the participant's endorsement rate, defining the proportion of items that were classified as grammatical (endorsed G items are correct responses, whereas endorsed NG items are incorrect). We complemented the analysis of behavioral data with estimates of accuracy and *d'* against chance levels by means of one-sample *t* tests.

Post-experimental data (questionnaires) were analyzed for indices of structural explicit knowledge: Verbal reports concerning awareness of rules were checked for consistency with the grammar (full consistence would indicate awareness), and the accuracy in generating grammatical sequences was computed (proportion of valid sequences, among the 10 sequences requested). Valid (grammatical) sequences were then analyzed one-by-one, so as to exclude generated sequences that had been presented during the acquisition or classification tasks. Our assumption was that the generation (recall) of sequences that were previously seen by participants is not a valid expression of structural knowledge because it may simply reflect participants' memory for concrete exemplars (see, e.g., Pothos, 2007). Memory for concrete exemplars is highly unlikely to account for eye-tracking sensitivity effects (response to violation letters) and is thus irrelevant for understanding our results. After excluding non-novel sequences, we were left with *generator participants* (those generating novel grammatical sequences) and *nongenerators* (generated none). Generators may be considered potential explicit learners but it may also not be the case: a small number of novel grammatical sequences may result from chunk memory (i.e., memory of frequent fragments, which may be concatenated as legal sequences by chance; see Pothos, 2007), and chunk memory is also irrelevant for understanding ocular responses to a violating letter. Still, we wanted to grant that the whole group's pattern of results did not reflect the influence of generators (*potential explicit learners*). To that end, we did a control analysis in which we considered the behavioral and eye-tracking data of nongenerators (*strict implicit learners*) separately. If nongenerators replicated the pattern of the whole group and survive the exclusion of potential explicit learners, this would be evidence that our pattern of findings reflects implicitly acquired knowledge.

## RESULTS

### BEHAVIORAL RESULTS

Accuracy was at chance levels in baseline preference ($M$ = 49%), $t(29) = -0.539$, $p > .59$, and above chance levels after exposure (final preference: $M$ = 59%, $t[29] = 4.32$, $p < .001$; grammaticality: $M$ = 63%, $t[29] = 4.85$, $p < .001$). Discrimination between G and NG sequences (difference between endorsement rates) increased after exposure (see Figure 2.2), as shown by a significant Test x Gram interaction for baseline preference against final preference (see Table 2.2). The non-significant Test x Gram x ACS interaction indicated that increased discrimination did not depend on ACS. The Test x ACS interaction was non-significant, ruling out ACS-based learning. Comparisons between final preference and grammaticality classification showed increased discrimination in the latter (see Table 2.3), and again there were no significant effects involving ACS. In line with this, *d'* did not differ significantly from zero in baseline preference (*M* = -0.045), *t*(29) = -0.56, *p* > .57, but it did so in final preference (*M* = 0.544), *t*[29] = 3.99, *p* < .001, and grammaticality (*M* = 0.878), *t*(29) = 4.75, *p* < .001. In summary, the results showed that the exposure to grammatical examples induced the acquisition of knowledge based on grammatical status and not on ACS, entirely consistent with previous findings (Folia et al., 2008; Folia & Petersson, 2014; Forkstam et al., 2008; Silva et al., 2016; Uddén et al., 2008).

Post-experimental verbal reports showed no evidence of explicit learning or awareness of the underlying grammar. Some participants reported decision criteria

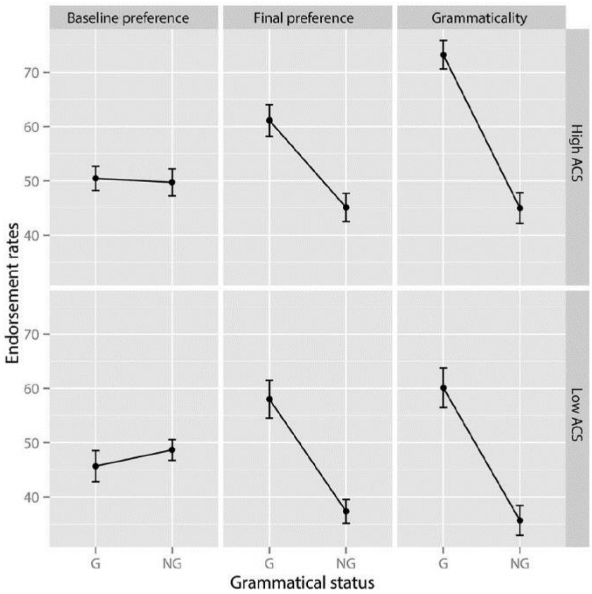


**FIGURE 2.2.** Mean endorsement rates (classification as grammatical) in Experiment 1 as a function of test, grammatical status (G = grammatical; NG = non-grammatical) and associative chunk strength (ACS). Error bars indicate the standard error of the mean.

other than gut-feeling (e.g., terminal letters), but these were never fully consistent with the grammar. In the sequence generation task, some participants generated valid (grammatical) sequences. However, only a few of these were novel relative to the acquisition and classification sets, suggesting that most sequences were memorized exemplars. Novel sequences were generated by 13 participants (17 generated none), and the mean accuracy level for the whole group was 7%. A closer inspection showed that the structure of the successfully generated novel sequences (as well as that of unsuccessfully generated ones) was based on the concatenation of frequent chunks (e.g., MS + VRX), indicating that the generation of novel sequences was based on memory for chunks rather than structural knowledge. Altogether, these facts strongly suggest that structural explicit knowledge did not take place. Nevertheless, we analyzed the behavioral accuracy levels for the nongenerators (17 participants with successful generation = 0) separately, so as to make sure that the global indices of knowledge were not expressing the performance of generators (generation > 0), who might be considered potential explicit learners under utmost skepticism. In line with our expectations, the accuracy of nongenerators (strict implicit learners) was at chance levels in baseline preference (*M* = 51%), *t*(16) = .298, *p* > .76, and above chance levels after exposure (final preference: *M* = 59%, *t*[16] = 4.07, *p* = .001; grammaticality: *M* = 62%, *t*[16] = 3.94, *p* = .001). Therefore, the grammar-based learning pattern observed in the whole group did not result from the influence of potential explicit learners. We repeated this control analysis for eye-tracking data, as shown subsequently.

Table 2.2

*Experiment 1: Comparison between Baseline Preference and Final Preference*

| Effect | Behavioral (endorsement rates) | Eye-tracking: First-fixation duration | Eye-tracking: Dwell time (proportion) | Eye-tracking: Fixation (proportion) | Eye-tracking: Dwell/first-fixation |
|---|---|---|---|---|---|
| Fixed effect | | | | | |
| Test x Gram x ACS | $X^2(2) = 1.63, p = .44$ | $X^2(2) = 1.17, p = .56$ | $X^2(2) = 7.46, p < .05$ | $X^2(2) = 14.0, p < .001$ | $X^2(2) = 0.48, p = .78$ |
| Test x Gram | $X^2(1) = 33.4, p < .001$ | $X^2(1) = 1.18, p = .28$ | $X^2(1) = 18.7, p < .001$ | $X^2(1) = 19.1, p < .001$ | $X^2(1) = 15.8, p < .001$ |
| Test x ACS | $X^2(1) = 0.58, p = .44$ | $X^2(1) = 0.03, p = .87$ | $X^2(1) = 0.14, p = .70$ | $X^2(1) = 0.14, p = .71$ | $X^2(1) = 1.89, p = .17$ |
| Random effect | Var (SD) | Var (SD) | Var (SD) | Var (SD) | Var (SD) |
| Participant (intercept) | 77.2 (8.79) | 651.8 (25.5) | 0.0003 (0.0173) | 0.0002 (0.0159) | 0.0240 (0.1551) |
| Residual | 326.6 (18.1) | 12060 (109.8) | 0.0044 (0.0662) | 0.0056 (0.07514) | 1.0529 (1.0261) |
| Number of observations | 480 | 4188 | 6095 | 6240 | 4246 |

*Note.* N = 30. Test = Baseline Preference vs. Final Preference; Gram = Grammatical status (grammatical vs. non-grammatical); ACS = Associative Chunk Strength (high vs. low); Var = variance.

## EYE-TRACKING RESULTS

The comparison between baseline preference and final preference showed increased post-exposure discrimination (significant Test x Gram interactions; see Figure 2.3 and Table 2.2) in all eye-tracking measures but first-fixation duration. Consistent with this, post hoc comparisons revealed significant differences between G and NG sequences in final preference for dwell time, $X^2$(1) = 77.8, *p* < .001, fixations, $X^2$(1) = 72.1, *p* < .001, and dwell/first-fixation, $X^2$(1) = 51.1, *p* < .001, but not for first-fixation duration (*p* > .14). At baseline preference, there were grammatical effects on dwell,

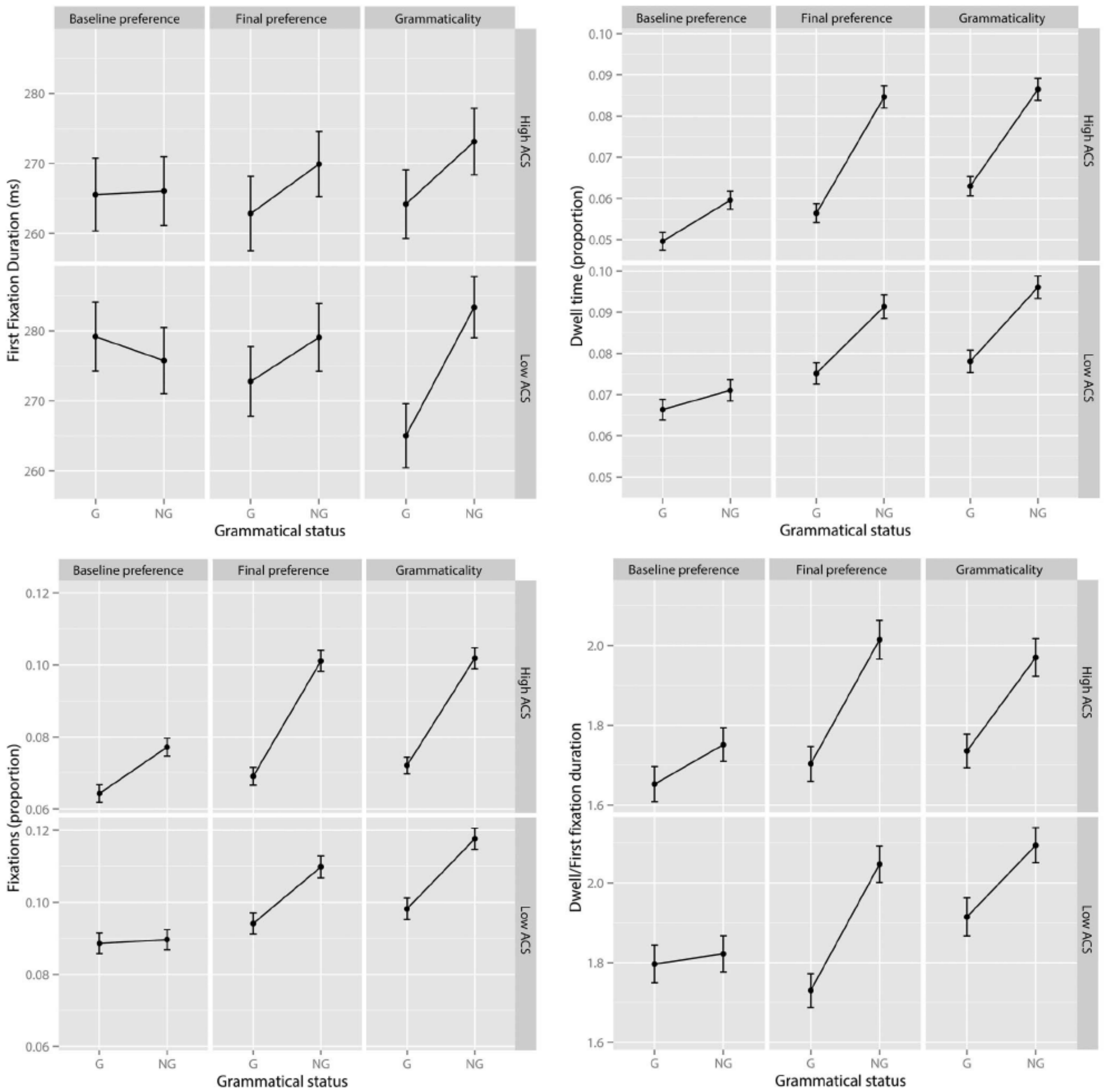


**FIGURE 2.3.** Mean eye-tracking measures for the target letter in Experiment 1 as a function of test, grammatical status (G = grammatical; NG = non-grammatical) and associative chunk strength (ACS). Error bars indicate the standard error of the mean.

$X^2(1) = 10.8$, $p < .001$, and fixations, $X^2(1) = 7.33$, $p < .01$, but not on dwell/first-fixation ($p > .18$) or first-fixation ($p > .91$). Comparisons between final preference and grammaticality (see Table 2.3) showed no changes. In both comparisons (baseline preference vs. final preference, final preference vs. grammaticality), there were significant Test x Gram x ACS interactions, but they were merely quantitative and did not affect the learning pattern. From baseline preference to final preference, discrimination increased for both High ACS (dwell: $X^2[1] = 16.7$, $p < .001$; fixations: $X^2[1] = 14.9$, $p < .001$) and Low ACS sequences (dwell: $X^2[1] = 5.06$ $p < .05$; fixations: $X^2[1] = 6.43$, $p < .05$), and from final preference to grammaticality it remained constant in both

ACS levels (High ACS: dwell: $X^2$[1] = 0.84, *p* = .36; fixations: $X^2$[1] = 0.16, *p* = .69; Low ACS: dwell: $X^2$[1] = 0.12, *p* = .73; fixations: $X^2$[1] = 0.42, *p* = .51). There was no evidence of ACS-based change (Test x ACS) in eye movements.

Table 2.3

*Experiment 1: Comparison between Final Preference and Grammaticality Classification*

| Effect | Behavioral (endorsement rates) | Eye-tracking | | | |
|---|---|---|---|---|---|
| | | First-fixation duration | Dwell time (proportion) | Fixation (proportion) | Dwell/first-fixation |
| Fixed effect | | | | | |
| Test x Gram x ACS | $X^2(2) = 1.26, p = .53$ | $X^2(2) = 1.17, p = .56$ | $X^2(2) = 7.46, p < .05$ | $X^2(2) = 12.6, p < .01$ | $X^2(2) = 0.48, p = .78$ |
| Test x Gram | $X^2(1) = 4.45, p < .05$ | $X^2(1) = 1.20, p = .27$ | $X^2(1) = 0.13, p = .72$ | $X^2(1) = 0.06, p = .81$ | $X^2(1) = 2.78, p = .10$ |
| Test x ACS | $X^2(1) = 2.32, p = .13$ | $X^2(1) = 0.58, p = .45$ | $X^2(1) = 0.14, p = .70$ | $X^2(1) = 1.11, p = .29$ | $X^2(1) = 3.80, p = .05$ |
| Random effect | Var (SD) | Var (SD) | Var (SD) | Var (SD) | Var (SD) |
| Participant (intercept) | 70.2 (8.38) | 580.7 (24.1) | 0.0003 (0.0183) | 0.0003 (0.0172) | 0.0278 (0.1666) |
| Residual | 428.6 (20.7) | 12023 (110) | 0.0048 (0.0649) | 0.0059 (0.0769) | 1.1184 (1.057) |
| Number of observations | 480 | 4425 | 6098 | 6264 | 4246 |

*Note.* N = 30. Test = Final Preference vs. Grammaticality Classification; Gram = Grammatical status (grammatical vs. non-grammatical); ACS = Associative Chunk Strength (high vs. low); Var = variance.

The ocular patterns of nongenerators (participants generating no valid sequences, n = 17) were similar to those of the whole group (see Figure 2.4). In the comparison between baseline preference and final preference, there were significant Test x Gram interactions for dwell time, $X^2$ (1) = 4.37, *p* = .036, number of fixations, $X^2$(1) = 4.92, *p* = .026, a marginal interaction for dwell/first fixation, $X^2$(1) = 2.81, *p* = .093, and no interaction for first fixation duration, $X^2$(1) = 1.73, *p* = .18. Interactions among test, grammaticality, and ACS were non-significant (all *p*s > .13), and so were Test x ACS interactions (all *p*s > .30). Comparisons between final preference and grammaticality classification showed non-significant effects.

## DISCUSSION

With the exception of first-fixation duration, all eye-tracking measures paralleled behavioral findings and showed increased discrimination between grammatical and non-grammatical sequences after exposure. Thus, eye-tracking measures showed sensitivity effects in our active forced-choice test. First-fixation duration did not show any significant sensitivity effects, an issue we return to in the General Discussion. Unlike behavioral measures, eye movements revealed no differences between preference and

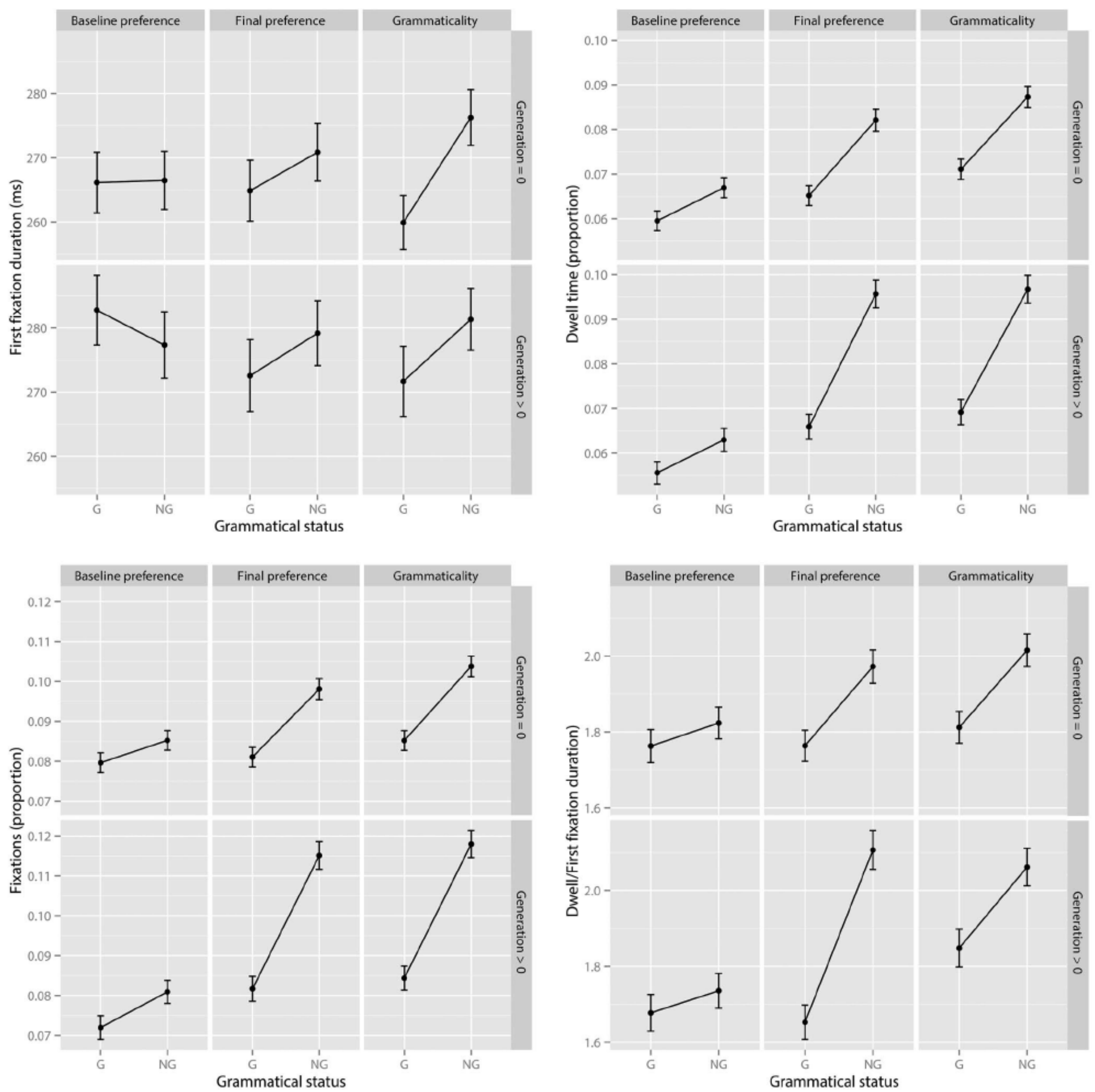


**FIGURE 2.4.** Mean eye-tracking measures for the target letter in Experiment 1 as a function of test, grammatical status (G = grammatical; NG = non-grammatical) and performance in the sequence generation task (between-subjects factor: nongenerators [generation = 0, n = 17] vs. generators [generation = 0, n = 13]). Error bars indicate the standard error of the mean.

grammaticality classification, suggesting that previous evidence of quantitative differences in the sensitivity of both tests (e.g., Folia et al., 2008) may reflect decision-related processes (see General Discussion). Neither behavioral nor eye-tracking results indicated learning based on surface features (ACS). The observed pattern of eye-tracking results remained after the exclusion of potential explicit learners. In summary, this experiment showed that eye movements capture the outcomes of implicit AGL when participants are engaged in an active, forced choice task. In Experiment 2, we test whether this is or is not the case during passive testing, where no instruction is provided.

## EXPERIMENT 2: EYE MOVEMENT IN PASSIVE TESTS

As in Experiment 1, we approached AGL with a proper-learning paradigm using passive tests (see Table 2.1). A group of participants different from that of Experiment 1 was exposed to the artificial grammar, and eye movements were recorded before and after exposure, under no instruction other than to look at the sequences. To reach a within-subjects comparison of test effects (passive vs. active), we added an active test upon completion of the experiment (see Table 2.1). If discriminative eye movements are facilitated by active tests, ocular discrimination should be less apparent in the present experiment compared with the previous one, and the introduction of an active test in the present experiment should boost discrimination.

### METHOD

#### PARTICIPANTS

Twenty-nine participants took part in the experiment, and 1 was excluded for excess of artifacts. The remaining 28 (*M* age ± *SD* = 25 ± 8; 23 female) complied with the selection criteria of Experiment 1.

#### STIMULUS MATERIALS

The grammar from Experiment 1 was used to generate one acquisition set (64 items) and seven test sets (16 x 4 = 64 items each). The structure of the stimulus material was identical to Experiment 1.

#### PROCEDURE

Participants were exposed to five acquisition sessions (see Table 2.1), on five different days. Sessions were approximately 20 min long. As in Experiment 1, they did same/different judgments on paired sequences (32 same/32 different, five different pairings across the five sessions). Before the first session, they underwent a passive baseline test, where eye-tracking measures were collected in response to 32 G and 32

NG sequences (16 high and 16 low ACS in each group). At the end of each acquisition session, a passive test was run (Passive Tests 1 through 5). In all passive tests, participants were instructed to look at the sequences. On Day 5, the passive test was followed by a grammaticality classification (active) test similar to Experiment 1.

### EYE-TRACKING DATA RECORDING AND PREPROCESSING

Data recording and preprocessing followed the steps described for Experiment 1. Artifact inspection led to the exclusion of 1 participant. The data points that entered the analyses (out of 10752 potential data points—28 participants x 64 items x 6 tests, for the first comparison; out of 3584 data points—28 participants x 64 items x 2 tests, for the other comparison) are quantified in Table 2.4 and Table 2.5, respectively.

### STATISTICAL ANALYSIS

The analysis was similar to that in Experiment 1. We focused on two different comparisons: across all passive tests (six levels for test factor), and between the last passive test and the active grammaticality test (two levels). In this experiment, behavioral data could not be analyzed with a proper learning approach because no active baseline was included. Therefore, we analyzed endorsement rates, accuracy and *d'* in the (single) active test of this experiment.

## RESULTS

### BEHAVIORAL RESULTS

Accuracy was significantly above chance levels (*M* = 65%), $t(27) = 4.99$, $p < .001$. Participants discriminated between grammatical and non-grammatical sequences in grammaticality classification (see Figure 2.5; gram: $X^2[2] = 48.1$, $p < .001$), and this was independent from ACS (Gram x ACS: $X^2[1] = 66.2$, $p = .18$). The *d'* was significantly different from zero (*M* = 0.90), $t(29) = 4.92$, $p < .001$.

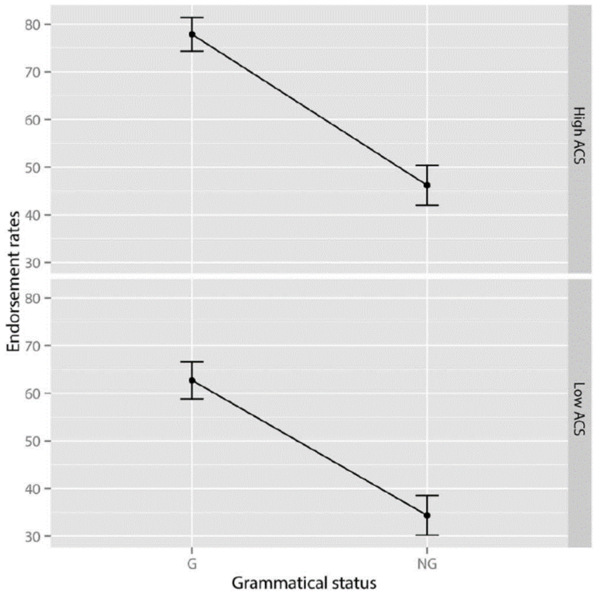


**FIGURE 2.5.** Mean endorsement rates (classification as grammatical) in Experiment 2 as a function of test, grammatical status (G = grammatical; NG = non-grammatical) and associative chunk strength (ACS). Error bars indicate the standard error of the mean.

Post-experimental data paralleled that of Experiment 1. Participants showed no evidence of explicit knowledge of the artificial grammar in their verbal reports, although some participants generated valid sequences. As in Experiment 1, only a few sequences were novel (*M* = 7% novel, correct sequences provided by 11 participants), and these were made up of frequent chunks. The accuracy level of nongenerators ($n$ = 17) in the grammaticality classification task was above chance (*M* = 59%), $t(16) = 2.52$, $p = .023$. As in Experiment 1, we analyzed separately the ocular patterns of these 17 nongenerators for control (see subsequent text).

EYE-TRACKING RESULTS

Discrimination based on grammatical status increased across passive tests (baseline plus five subsequent tests) for the proportion of dwell time and dwell-to-first-fixation ratio (see Figure 2.6 and Table 2.4). There were also marginal changes for the proportion of fixations. Nevertheless, individual comparisons between baseline and each subsequent test indicated significant differences in only one case, namely for dwell time on Day 4 against baseline ($b = 0.0105$, $SE = 0.00519$, $t = 2.02$).

Table 2.4

*Experiment 2: Comparison across Passive Tests (Passive Baseline and Passive Tests 1 Through 5)*

| Effect | First-fixation duration | Fixation (proportion) | Dwell time (proportion) | Dwell/first-fixation |
|---|---|---|---|---|
| Fixed effect | | | | |
| Test x Gram x ACS | $X^2(6) = 2.41, p = .88$ | $X^2(6) = 3.73, p = .71$ | $X^2(6) = 4.05, p = .67$ | $X^2(6) = 3.53, p = .74$ |
| Test x Gram | $X^2(5) = 5.72, p = .33$ | $X^2(5) = 9.35, p = .10$ | $X^2(5) = 14.1, p < .05$ | $X^2(5) = 11.2, p < .05$ |
| Test x ACS | $X^2(5) = 4.07, p = .54$ | $X^2(5) = 5.89, p = .32$ | $X^2(5) = 6.19, p = .29$ | $X^2(5) = 3.24, p = .66$ |
| Random effect | Var (SD) | Var (SD) | Var (SD) | Var (SD) |
| Participant (intercept) | 1245 (35.3) | 0.00016 (0.01246) | 0.00012 (0.01082) | 22020 (0.04849) |
| Residual | 11597 (107.7) | 0.00382 (0.06180) | 0.00260 (0.05095) | 1.45024 (1.20430) |
| Number of observations | 7034 | 9032 | 8820 | 6869 |

*Note.* N = 28. Test = Passive Baseline vs. Passive Tests 1 through 5; Gram = Grammatical status (grammatical vs. non-grammatical); ACS = Associative Chunk Strength (high vs. low); Var = variance.

Nongenerators alone (participants generating zero valid sequences, *n* = 17) were not able to fully provide the pattern of Test x Gram interactions seen for the whole group (see Figure 2.7): The interaction was marginal for dwell time, $X^2$(1) = 10.33, *p* = .066, and non-significant for fixations (*p* > .14) as well as dwell/first-fixation time (*p* > .46). For dwell time and number of fixations, this seemed to be due to loss of statistical power because the group of generators (participants generating valid sequences, *n* = 11) showed even fewer significant interactions (dwell: *p* > .50; fixations: *p* > .61). Thus, the ocular pattern of generators (potential explicit learners) does not seem to have been responsible for the results of the whole group. A different scenario showed up for dwell/first-fixation, where the Test x Gram interaction was significant for generators, $X^2$(1) = 13.38, *p* = .023, and non-significant for nongenerators (*p* > .46). Still, the interaction among test, grammaticality, and generation (generators vs. nongenerators) was non-significant, $X^2$(1) = 6.38, *p* > .38. For nongenerators, the interaction among test, grammaticality, and ACS was never significant (all *p*s > .40), and so was the interaction between test and ACS (all *p*s > .09).

Comparisons between Passive Test 5 and the active grammaticality test that was performed immediately after (see Table 2.5) revealed significant increases in discrimination for first-fixation duration and proportion of dwell time. There was a marginal increase for proportion of fixations. Consistent with the learning profile signaled by interactions, passive baseline did not show any grammaticality effects (*p*s > .31), Passive Tests 1 through 5 (collapsed) showed significant grammaticality effects on

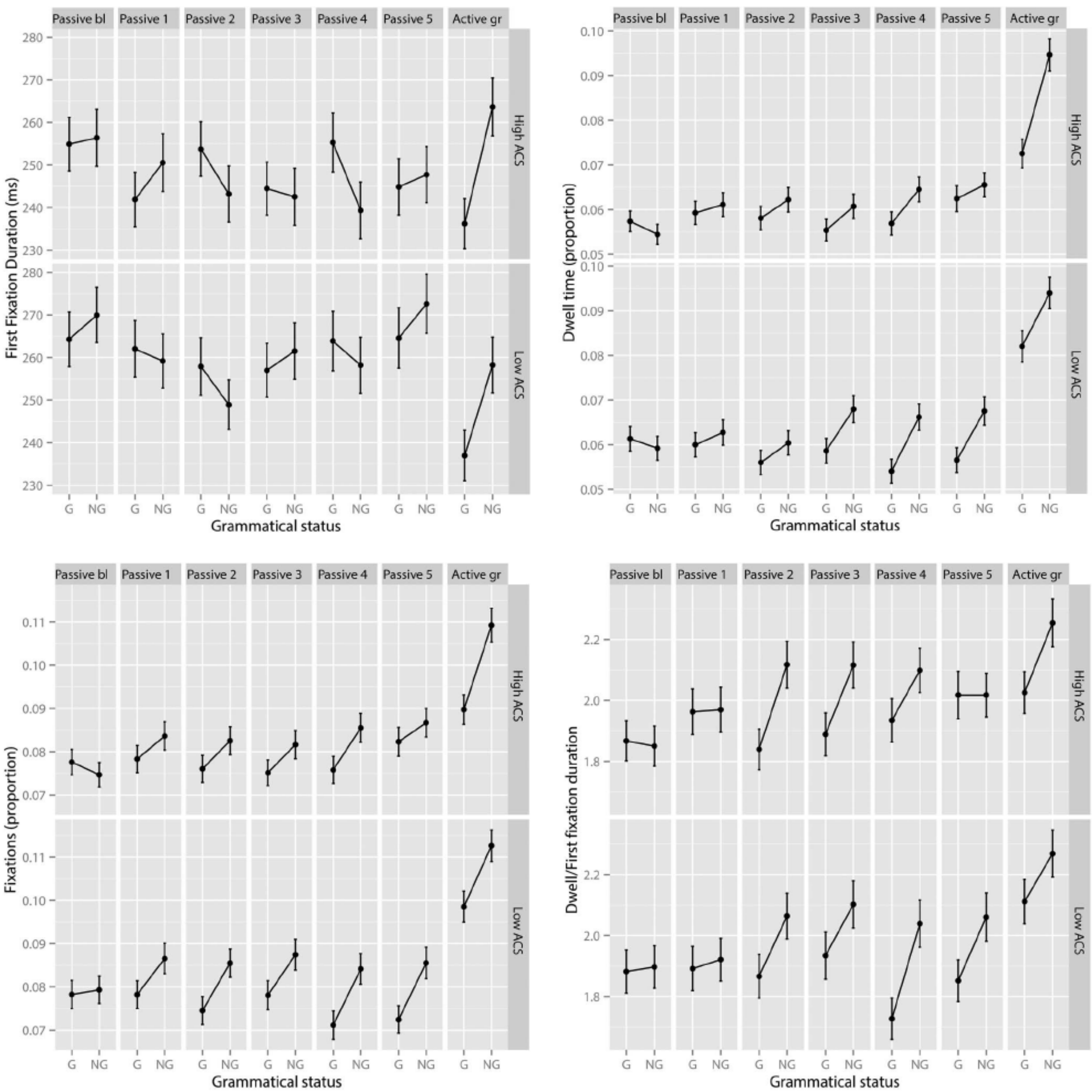


**FIGURE 2.6.** Mean eye-tracking measures for the target letter in Experiment 2 as a function of test (Passive bl = passive baseline; Passive 1–5 = Passive Tests 1 through 5; Active gr = active grammaticality classification), grammatical status (G = grammatical; NG = non-grammatical) and associative chunk strength (ACS). Error bars indicate the standard error of the mean.

dwell time, $X^2(1) = 24.9$, $p < .001$, fixations, $X^2(1) = 34.9$, $p < .001$, and dwell/first-fixation, $X^2(1) = 24.8$, $p < .001$, but not on first-fixation duration ($p > .44$), and the active grammaticality test showed significant grammaticality effects on all measures (first-fixation: $X^2[1] = 14.4$, $p < .001$; dwell: $X^2[1] = 24.4$, $p < .001$; fixations: $X^2[1] = 21.2$, $p < .001$; dwell/first-fixation: $X^2[1] = 7.82$, $p < .001$).

Nongenerators alone did not show the grammaticality-related changes of the whole group (dwell: $p > .22$; fixations: $p > .16$; first-fixation: $p > .12$), but generators alone did not show it either (dwell: $p > .11$; fixations: $p > .33$; first-fixation: $p > .16$). So, once again, the global pattern of results was not due to the influence of generators. Nongenerators showed no Test x Gram x ACS interactions ($p$ > .05), and they showed a significant Test x ACS interaction for first-fixation duration ($p$ > .05).

Table 2.5

*Experiment 2: Comparison between Passive Test 5 and Grammaticality Classification*

| Effect | First-fixation duration | Fixation (proportion) | Dwell time (proportion) | Dwell/first-fixation |
|---|---|---|---|---|
| Fixed effect | | | | |
| Test x Gram x ACS | $X^2(2) = 0.59, p = .74$ | $X^2(2) = 2.56, p = .28$ | $X^2(2) = 4.86, p = .09$ | $X^2(2) = 2.27, p = .32$ |
| Test x Gram | $X^2(1) = 4.30, p < .50$ | $X^2(1) = 2.81, p = .09$ | $X^2(1) = 5.07, p < .05$ | $X^2(1) = 0.77, p = .38$ |
| Test x ACS | $X^2(1) = 5.45, p < .05$ | $X^2(1) = 5.22, p < .05$ | $X^2(1) = 1.87, p = .17$ | $X^2(1) = 0.99, p = .32$ |
| Random effect | Var (SD) | Var (SD) | Var (SD) | Var (SD) |
| Participant (intercept) | 1502 (38.8) | 0.00020 (0.01421) | 0.00019 (0.01380) | 0.03600 (0.18970) |
| Residual | 11462 (107.1) | 0.00443 (0.06657) | 0.00344 (0.05864) | 1.57400 (1.25440) |
| Number of observations | 2368 | 3020 | 2892 | 2329 |

*Note.* N = 28. Test = Passive Test 5 vs. Grammaticality; Gram = Grammatical status (grammatical vs. non-grammatical); ACS = Associative Chunk Strength (high vs. low); Var = variance.

## DISCUSSION

As predicted, the absence of an active test weakened ocular discrimination. Compared with Experiment 1 (eye-tracking coupled with an active task), the Test x Grammatical status interactions— which once again excluded first-pass measures— were less significant for the passive tests in Experiment 2. For proportion of fixations, the effect went from significant to marginally significant. Critically, introducing an active test immediately after the last passive test boosted ocular discrimination in three of the four measures (first-fixation duration, proportion of dwell time, and proportion of fixations). Therefore, an active test seems to facilitate the ocular expression of artificial grammar learning. Similar to Experiment 1, the eye-tracking pattern observed in the whole group did not result from the influence of potential explicit learners, with a possible exception from dwell/first-fixation. We return to this issue in the General Discussion.

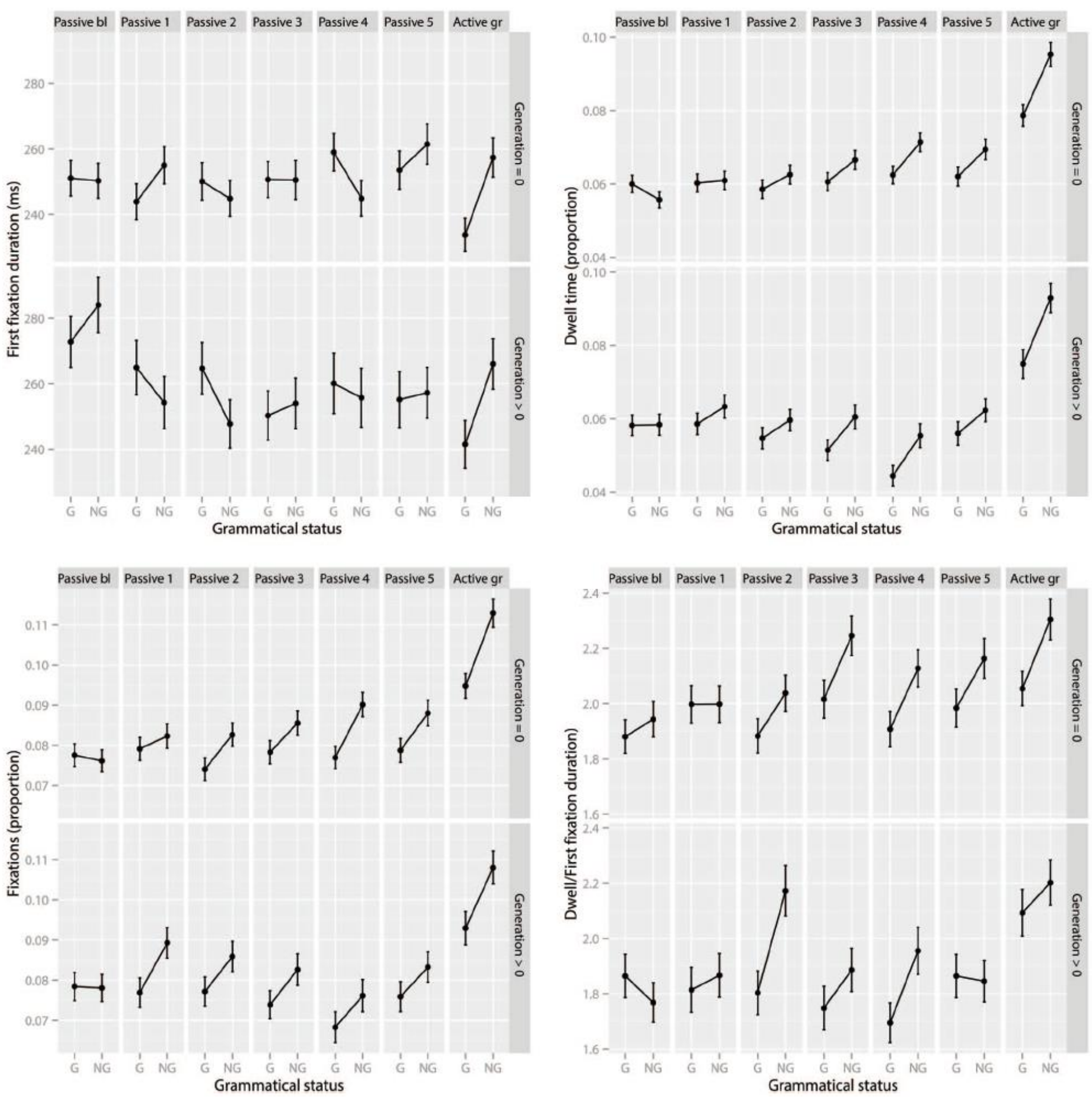


**FIGURE 2.7.** Mean eye-tracking measures for the target letter in Experiment 2 as a function of test, grammatical status (G = grammatical; NG = non-grammatical), and performance in the sequence generation task (between-subjects factor: nongenerators [generation = 0, n = 17] vs. generators [generation = 0, n = 11]). Error bars indicate the standard error of the mean.

## GENERAL DISCUSSION

In this study, we wanted to determine whether eye-tracking captures the implicitly acquired knowledge of an artificial grammar and shed light on some restrictions to this possibility. Our first goal was to test the hypothesis that an eye-tracking AGL test shows more robust discrimination between grammatical and non-grammatical sequences when it is coupled to an active test than when this is not the case. In line with our hypothesis, eye movements were significantly sensitive to the outcomes of implicit AGL during both the active final preference classification (Experiment 1) and the active grammaticality classification (Experiments 1 and 2), but less during passive tests, when no instructions were provided other than looking at the sequences (Experiment 2). In addition, eye movements reflected the knowledge of participants who showed no awareness of the grammar by all standards (verbal reports, sequence generation, performance in preference, implicit tests). Thus, we showed that eye-tracking measures alone are able to capture the outcomes of implicit artificial grammar learning and that the sensitivity of eye-tracking measures to implicit knowledge is boosted in the presence of an active forced-choice task.

The most important contribution of our study was to show that implicitly acquired AG knowledge may be captured with eye-tracking. Capturing implicit AGL outcomes in humans with eye-tracking measures has failed in previous studies. Wilson and colleagues (2015) found null results when using an auditory paradigm probing ocular responses to the whole sequence, and it was suggested that eye-tracking-only, passive tests are unable to capture AG knowledge in humans. In line with this, Heaver (2012) probed pupillary responses to visual (whole) AG sequences and also found null results. In both studies, behavioral discrimination was observed after exposure, suggesting that knowledge had been acquired but it was not being properly captured by eye-tracking measures. Drawing on sensitivity effects, which rely on responses to the violating event rather than the whole sequence, we captured eye-tracking signatures of implicitly acquired AG knowledge.

The sensitivity of eye-tracking measures to implicit artificial grammar learning occurred in the expected direction, that is, as post-exposure increases in proportion of dwell time, proportion of fixations and dwell-to-first fixation ratio for non-grammatical target letters. The presence of sensitivity effects in AGL tests, paralleling the ones observed in tests of natural syntax knowledge, is consistent with the idea that the outcome of AGL is structural, syntax-like knowledge (Christiansen et al., 2012, 2010; Conway et al., 2007; Lelekov-Boissard & Dominey, 2002; Silva et al., 2016; Tabullo et al., 2013; Zimmerer et al., 2014).

Eye-tracking measures were not sensitive to the learning of subsequences (ACS). ACS effects on eye movements were not expected from the behavioral results of Experiment 1 because these showed no ACS-based learning (no Test x ACS interactions), in line with previous studies of ours (Folia et al., 2008; Folia & Petersson, 2014; Forkstam et al., 2008; Silva et al., 2016; Uddén et al., 2012). However, even if behavioral ACS effects on endorsement rates had been observed, it is unclear whether ocular effects on a single violating letter would also be observed. The ACS of a letter sequence presented at the final test phase quantifies how often the bigrams and trigrams of that sequence appeared at the exposure phase, and thus it concerns units larger than one single letter. Therefore, there might be a lack of sensitivity in this respect. Nevertheless, this lack of local subsequence familiarity (ACS) effect is consistent with previous and current behavioral results.

Our second goal was to determine specific eye-tracking signatures of implicitly acquired knowledge. Previous literature has suggested that implicit knowledge on structured sequences, including natural syntax, is better expressed in first-pass eye-tracking measures compared with second-pass measures. Going against this expectation, whole-trial measures (dwell time and number of fixations) revealed AG knowledge in both the active and passive conditions (Experiment 1 and 2) of our study, whereas first-pass measures (first-fixation duration) did not. Critically, we ruled out the possibility that this eye-tracking pattern resulted from explicit learning. Concerning dwell/first-fixation (second-pass measure), we saw sensitivity to acquired knowledge, but our results were not clear as to whether it reflected knowledge that may be considered implicit beyond any doubt: In Experiment 2, unsuccessful generators (strict implicit learners) did not show learning effects on dwell/first fixation, whereas successful generators (potential explicit learners) did so. Moreover, in Experiment 1, the significant interaction for the whole group became marginal after the exclusion of potential explicit learners. Therefore, for second-pass measures (dwell/first-fixation), two different scenarios seem possible: Either our potential explicit learners were effectively explicit and dwell/first-fixation reflects mostly explicit knowledge as suggested in the literature, or these learners were actually implicit and second-pass measures may express implicitly acquired knowledge. As we stressed throughout this article, the first scenario is unlikely: Potential explicit learners performed above chance levels in the preference classification test (an implicit behavioral test), they did not show awareness of the grammar in their verbal reports, they generated only a small amount of novel grammatical sequences, and these novel sequences could be explained by memory for chunks rather than structural knowledge. Therefore, the most likely scenario is that all participants— even those who generated new strings—acquired implicit knowledge, that dwell/first-fixation patterns reflect implicit knowledge, and some reason other than explicit learning made successful generators more responsive in terms of second-pass eye signatures. In this view, the assumption of a strong association between implicit knowledge and first-pass reading (Godfroid et al., 2015) may be premature, either because second-pass reading is not always a reflection of controlled (vs. automatic) processing or because cognitive control is not incompatible with access to implicitly acquired knowledge (Schott et al., 2005).

Finally, concerning the reasons why an active test boosts ocular discrimination, these remain unspecified. One could think that repeated testing throughout the learning phase (alternate learn-test design, Experiment 2) would introduce noise by forcing participants to process a repeated proportion of non-grammatical sequences, thus leading to weaker learning outcomes. Alternate designs have been shown to elicit weaker learning results when compared with continuous learning designs (Citron, Oberecker, Friederici, & Mueller, 2011) as the one we used in Experiment 1 (but see Forkstam et al., 2006). However, the behavioral and the eye-tracking results of the active test (immediately following passive tests in Experiment 2) provided evidence that knowledge was being concealed - rather than impeded - by passive tests. Earlier in this article, we raised two possible explanations for why passive tests may conceal acquired knowledge: either passive, eye-tracking-only tests are generally unable to provide optimal levels of attention because there is no goal other than looking at the sequences, or passive tests do not specifically elicit the syntactic (structure-related) analysis of AGL sequences needed for expressing knowledge. Further work on this issue should compare eye-tracking sensitivity to AGL classification instructions that activate syntactic analysis to different degrees (e.g., instructions focusing on the visual properties of letters may weaken syntactic analysis).

## CONCLUSION

Our results are novel in showing that eye-tracking measures alone are able to express the implicit knowledge resulting from learning an artificial grammar, even though adding an active, forced-choice test boosts ocular discrimination. The possibility of using instruction-free settings such as eye-tracking to measure the outcomes of implicit structured sequence learning opens new avenues in research. When using eye-tracking concurrently with two different forced-choice active tests, preference and grammaticality classification, we also found highly similar eye-movement profiles. This overcomes behavioral differences observed so far and indicates that differences observed in behavioral testing may result from processes related to final decisions, namely participants' self-monitoring of response direction. Finally, our findings suggest that whole-trial measures may be relevant, and even crucial, to capture the outcomes of implicit structured sequence learning.

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# CHAPTER THREE

## STUDY 2 - Statistical learning is related to implicit orthographic knowledge and reading proficiency


### ABSTRACT

Several studies of reading suggest that statistical learning might contribute to the acquisition of literacy competences. In this study, we aimed to investigate if there is a relationship between statistical learning and three literacy measures. Eighty-five Portuguese adults performed a statistical learning task, two different implicit orthographic knowledge tasks (where the frequency of orthographic patterns was manipulated) and a reading fluency task. Results showed that participants chose the most frequent orthographic pattern, although without awareness of such trend. Nevertheless, the implicit orthographic knowledge tasks correlated differently with the statistical learning task: while a significant correlation with an implicit orthographic knowledge decision task was observed, the same result was not observed in a pseudoword dictation task. Reading performance was also significantly correlated with statistical learning, suggesting a contribution of implicit learning to reading proficiency in an orthography more transparent than English. Furthermore, statistical learning seems to boost the impact of exposure to print on reading fluency. These results suggest a role of implicit learning capacity in the extraction the written language regularities and in the improvement of literacy skills.

## INTRODUCTION

It has been proposed that proficiency in reading and writing depends on implicit processes beyond the conscious effort to learn (Arciuli, 2018; Ehri, 2005; Seidenberg, 2014; Treiman, 2018). However, the relationship between implicit processes and reading and writing skills is not yet fully characterized. In the present study, we explore this relationship in an effort to better understand if an ability to extract environmental regularities is related to reading proficiency and to the implicit knowledge of orthographic patterns.

Statistical learning refers to the capacity to acquire aspects of probabilistic spatio-temporal associations present in a wide range of input stimuli and occurs without awareness or intention to learn (Pierre Perruchet & Pacton, 2006). From an early age, and before formal instruction begins, children can implicitly pick up visual patterns in written text they are exposed to, including the arrangement and sequencing of elements (Pacton, Fayol, & Perruchet, 2005a; Treiman, Gordon, Boada, Peterson, & Pennington, 2014; Treiman, Kessler, Boland, Clocksin, & Chen, 2017; Tucker, Castles, Laroche, & Deacon, 2016). Thus, part of learning to read and write could involve abstracting structure and regularities from text exposure and contribute to the development of reading and writing proficiently (Steffler, 2001). According to this perspective, during reading and writing acquisition children implicitly extract a variety of information from text exposure that can be described as rules (e.g. in Portuguese, consonants cannot be doubled in the beginning of a word), letter specific properties (e.g. the *s* can be doubled in the middle of a word, but the *h* cannot) and probabilistic properties (e.g. the sound [ʃ][1] after the diphthong [a:ɪ] is more commonly spelled with a <x> than with <ch>) (Deacon, Conrad, & Pacton, 2008; Sébastien Pacton, Borchardt, Treiman, Lété, & Fayol, 2014; Pacton et al., 2005).

[1] We used the International Phonetic Association notational standard for the phonetic representation

Orthographic knowledge refers to the representation of spoken language in written form, stored in memory (Apel, 2011) and has an impact on reading and writing proficiency (Ehri, 2005). The grapheme-phoneme correspondences are typically acquired through explicit instruction, but aspects can also be picked up implicitly through exposure to written language (Ehri, 2005). In fact, although many phonological, orthographic and morphological rules that enable us to write correctly are taught explicitly during literacy acquisition, the number and complexity of the combinations that the written language presents and that are required to become a proficient speller are very large and thus statistical learning may play a role in acquisition (Steffler, 2001).

It has been suggested that exposure to written text is critical to reading efficiency (Protopapas et al., 2017) and to spelling competence (Pacton et al., 2014). Recently, Protopapas and collaborators (2017) explored the role of incidental exposure to print, without requiring explicit reading, in orthographic learning. The authors found that reading and spelling performance for targeted words were substantially enhanced after increased exposure to training items. Furthermore, this knowledge was also generalized to words with similar properties (same derivational affixes) and were long lasting (observed after a week), demonstrating that exposure to print per se improve reading and spelling skills (Protopapas et al., 2017).

However, orthographic knowledge refers not only to word-level orthographic representations but also to orthographic pattern knowledge, that is, specific letter combinations and constraints within words (Apel, 2011). According to several studies (Deacon et al., 2008; Pacton et al., 2014, 2005; Treiman & Wolter, 2018) knowledge of these patterns might be acquired by exposure to text. The use of a certain spelling arrangement among several possibilities for the same phoneme has been associated with the frequency that it occurs or with the frequency with which letters co-occur. Furthermore, the impact of statistically learned orthographic regularities could modulate the use morphological rules and explicitly acquired, taught rules (Deacon et al., 2008; Pacton et al., 2005). Several studies have shown that the context can influence people’s decisions about the spelling they choose to resolve an ambiguity (Pacton et al., 2005; Treiman & Boland, 2017; Treiman & Wolter, 2018). According to Steffler (2004), the decision to use of one spelling over another is frequently implicit, as we are not aware of the orthographic convention that underlies certain spelling structures. In the present study, we tested the implicit knowledge of these orthographic patterns incorporated in pseudowords in a forced-choice task and a spelling task. In these tasks, the phonemes selected can be correctly spelled in two different ways, but one is clearly more frequent than the other in the Portuguese lexicon (for example, the sound [a:ɪ ʃ] could be correctly spelled with either <x> or <ch>, but it is more frequent to find words spelled with <aix> than with <aich>). Although the frequency of these orthographic patterns is different, this difference is not explicitly taught. The frequent pattern must then be acquired implicitly by exposure and the infrequent use of the alternative spelling pattern could be achieved through word-specific memorization (Deacon et al., 2008). Therefore, if statistical learning plays a role in the acquisition of these patterns (Pacton, Perruchet, Fayol, & Cleeremans, 2001; Pacton et al., 2014; Treiman & Wolter, 2018), participants will tend to choose the more frequent pattern. In children, It has been shown that a correlation between the knowledge of the doubling rule in spelling and implicit learning capacity is significant, suggesting that the ability to abstract patterns is correlated with spelling ability (Steffler, 2004). Therefore, we expected that participants with a better statistical learning ability would show a higher sensitivity to these orthographic regularities, resulting in a better performance in both the forced-choice and pseudoword spelling task.

### STATISTICAL LEARNING AND READING PROFICIENCY

Reading acquisition implies to learn and automatize the correspondences between letters and phonemes. Although these correspondences are mostly explicitly taught, not every correspondence is taught and the automatization of the mapping between graphemes and phonemes also rely on statistical learning through regular exposure to text (Stoodley & Stein, 2011a). As children progress in their reading abilities, they get more exposure to written language and consequently become sensitive to contextual cues such as the co-occurrence of letters (Ehri, 2005). There are several statistical regularities that are extracted and used without awareness. It has been showed that there are several probabilistic orthographic cues to lexical stress in word beginnings and word endings that adult and children are sensitive to that are not taught (for a review see Arciuli, 2018). For example, children learning Portuguese acquire knowledge that words with the letter <o> in the stressed syllable, despite rarely being accentuated, should be read as [o] or [ɔ]; as far as we know, this is not explicitly brought to their attention during formal instruction.

Furthermore, statistical learning has been associated with vocabulary growth (Evans, Saffran, & Robe-torres, 2009), vocabulary knowledge, oral language skills and phonological processing (Spencer, Kaschak, Jones, & Lonigan, 2015), which can boost reading performance (Arciuli & Simpson, 2012b).

In the last decade, several studies have examined the link between implicit learning and reading in dyslexic adults and children (e.g. Kahta & Schiff, 2016; Laasonen et al., 2014). These studies suggest that poor implicit learning could hamper the establishment of adequate phonological processing as well as learning orthographic-phonological representations. Therefore, dyslexics might present a combination of a phonological deficit with an impaired sequence learning system that manifested in a failure to abstract the probabilistic regularities present in the grapheme-phoneme correspondences leading to reading difficulties (Howard et al., 2006). However, there is no consensus that dyslexia is associated with an implicit learning deficit (see, for example, Inácio et al., 2018; Lum, Ullman, & Conti-Ramsden, 2013; van Witteloostuijn, Boersma, Wijnen, & Rispens, 2017) and therefore it is difficult to draw conclusions about the relationship between reading abilities and implicit learning capacities. In typical readers, it has been shown that a variability in statistical learning capacity is moderately related to reading performance, both in adults and children (Arciuli & Simpson, 2012b). However, Nigro, Jiménez-Fernández, Simpson, and Defior (2015) were not able to find a correlation between reading and implicit learning abilities and suggested that this association is present only in English, an opaque orthography. In transparent orthographies such as Spanish, the language used in the Nigro et al. (2015) study, this relationship might not be present.

In the present study, we aimed to replicate the Arciuli and Simpson (2012) findings in a more transparent orthography (Seymour et al., 2003), by presenting to typical Portuguese readers the same statistical learning task as they used and a reading task, to investigate whether the relationship between reading and implicit learning only emerges in opaque orthographies.

Additionally, we explored the role of statistical learning skills on the relationship between exposure to print, reading and orthographical knowledge. Therefore, we designed a reading habits questionnaire, with several questions aiming to quantify present and past exposure to print. We predicted that exposure to text has an influence on reading skills and orthographical knowledge and that this influence is boosted by individual statistical learning skills.

## METHOD

### PARTICIPANTS

Eighty-five undergraduate students (60 females; aged between 18 and 44; mean ± SD = 21.6 ± 5.0 years; grade mean ± SD = 13.4 ± 2.2) participated in this study in return for course credits. All participants were native Portuguese speakers with normal or corrected-to-normal vision and none indicated a history of head injury or other neurological or psychiatric problems. Participants read and signed an informed consent form describing the procedures, which adhered to the guidelines set out by the Declaration of Helsinki.

### STIMULUS MATERIAL

#### Statistical Learning task

The statistical learning task used was a slightly modified version of Arciuli & Simpson's task (2011, 2012). This task comprises an exposure phase and a test phase. The stimuli used in both phases were eighteen drawings of “monsters” specifically designed so they do not resemble any known cartoon character and hence cannot be easily labelled. Six of these monsters were used as practice items and the remaining twelve were grouped in four *base triplets* (named *ABC*, *DEF*, *GHI*, *JKL*, see Appendix).

In the *exposure phase* participants engage in a covert task where they were exposed to a continuous stream of monsters, presented one at a time for 400 ms with an interstimulus interval of 200 ms. The base triplets were embedded in this sequence: the three monsters from a triplet were shown sequentially before a new triplet appears and so on, until the complete sequence was displayed; the order of the monsters within triplets was fixed (e.g., for triplet *ABC*, the monster A was always displayed before B, and B before C). Each base triplet appeared 24 times. The order of the triplets in the exposure stream was randomized with two constrains: neither consecutive repeated triplets (e.g. … *ABCABC* …) nor repeated sequences of two triplets (e.g. … *ABCDEFABCDEF* …) were allowed. To ensure that participants were paying attention to the exposure phase, participants pressed a button whenever they saw a repeated monster. Hence, in six of the 24 appearances of each triplet, the initial or the final monsters were presented twice in a row (e.g. three occurrences of AABC and three occurrences of ABCC). We choose not to repeat the middle element of the triplet in order not to break the base triplet.

For the *test phase*, four new triplets were created with the same monsters, but ordered in a way that never appeared during the exposure phase. These four *new triplets* contained one monster of each of three base triplets (referred as *AEI*, *DHL*, *GKC* and *JBF*). In this way, the transitional probability (probability of event B occur after event A) of the internal pairs inside the new triplets based on the exposure phase was zero, clearly contrasting with the transitional probability for the internal pairs inside the base triplets that was .945 (not 1 because of the repetition of some elements of the base triplet for the cover task). In each trial of the test phase, a sequence of six monsters (a base triplet presented together with a new triplet) was presented, one at a time, with the same pace as during the exposure phase, but with a 1000 ms gap between the two triplets. Afterwards, a screen appeared asking participants to choose, in a self-paced manner, which of the two previous triplets had appeared in the exposure phase. Each base triplet was presented with each new triplet, creating 16 pairs of base-new triplets. These 16 pairs were displayed on four separate occasions, in a randomized and counterbalanced order, in a total of 64 trials. Both base triplets and new triplets were seen 16 times each.

### Implicit Orthographic Knowledge tasks

In order to assess the implicit orthographic knowledge of the participants we first evaluated the frequency of European Portuguese orthographic patterns associated with certain phonemes. Specifically, we searched for distributional asymmetries in two alternative orthographic patterns that can be used to represent a specific phoneme. For example, in the European Portuguese, the phoneme [ʃ] can be graphed as <x> or <ch>, but after the diphthong [a:ɪ] it is more frequent to use <x> (<aix> is more frequent than <aich>, although both are allowed). These distributional asymmetries do not obey to any specific rule and neither are taught explicitly during formal training. Any sensitivity to these asymmetries will therefore be acquired implicitly throughout the exposure to printed text. Using the European Portuguese word frequency database P-Pal (Soares et al., 2014), we searched for cases where there was a clear asymmetric preference for using one of two possible graphemes for the same phoneme (for example, the absolute frequency of <auch> is 151 whether the frequency of <aux> is 10209). Forty-one different cases were selected where this asymmetry was expressed by an frequency difference > 2198 occurrences in the lexical database. Pseudowords were created to incorporate these and used in two tasks designed to assess implicit orthographic knowledge. All pseudowords had three to four syllables and none had orthographic neighbors, in order to not resemble any real word and thus be selected or written by analogy, which would reveal a different type of implicit memory (Steffler, 2001).

In the *Implicit Orthographic Knowledge Decision task,* the two possible forms were presented on a computer screen and participants were instructed to select the one that seemed more orthographically accurate if it was a real Portuguese word (e.g. *mupaixo vs. mupaicho*). In this task, two different pseudowords were presented for each case, counter balancing the right-left presentation of each case. In total, the stimulus set comprises 82 pseudowords that were randomly presented to participants. We scored 1 if the participant chooses the most frequent orthographic representation and 0 if he/she selected the less frequent orthographic representation.

In the second task, *Dictation of Pseudowords*, participants heard an audio record of 41 new pseudowords with same cases as the previous task and had to write them down. The presentation of the items was randomized and the task self-paced:

participants heard the pseudoword, wrote it down and then pressed the space bar of the computer to hear the next pseudoword. Participants were instructed to write the pseudoword in a way they thought was correct. We scored 1 if the participant wrote the pseudoword using the most frequent orthographic representation and 0 if he/she wrote the less frequent orthographic representation.

**Reading task**

We used the 3DM reading test (Andreia Pacheco et al., 2014) to assess the participants' reading skills. This test is a time-limited reading-aloud task composed of three lists of words and pseudowords, presented in a fixed order. Participants were asked to read aloud as fast and accurately as possible the stimuli presented in the computer screen (for 30 s per list). The number of correctly read words per second was taken as the reading fluency measure.

**Reading Habits Questionnaire**

A questionnaire was constructed to assess the reading habits of the participants, as an indirect measure of the exposure to print. Participants were asked how many minutes of the previous month they spent reading material from several sources (e.g., novels, technical text, movie subtitles, blogs, news, etc.), both in digital and printed form. Additionally, some questions were asked about exposure to text in earlier years (e.g., how many books they had at home around the age of 14; if their parents read for them during childhood; how frequently participants saw their relatives reading). The questionnaire was sent by email to all 85 participants and 76 responded (89%).

PROCEDURE

The statistical learning task was presented as an attention task (covert task) and participants were instructed to press the space bar whenever they detected two equal monsters in a row within a continuous presentation stream of different monsters. After this exposure phase, participants were informed that the monsters they saw were in fact lined up in groups of three fixed elements. During the test phase, participants had to choose which of two groups of three monsters was lined together in the previous task. Participants were advised to follow their gut feeling and not overthink or try to analyze the triplets in the test phase.

After the statistical learning task, participants performed the reading task and the two implicit orthographic knowledge tasks. Half of the participants performed the implicit orthographic knowledge task first and then the dictation of pseudowords task and the other half of the participants did the opposite. All tasks were preceded by a practice trial and testing would only proceed if the experimenter was sure that the instructions were understood. Participants were informally interviewed after each task to assess if they had explicit knowledge of the implicit characteristics of the stimuli (both in the statistical learning task and in the implicit orthographical knowledge tasks). Subsequently to the testing, participants were asked to fill an online questionnaire to assess their reading habits.

**RESULTS**

Accuracy in the *Statistical Learning exposure phase* ranged from 29 to 100%, with a mean of 71% (±SD = 18). A lower score on this task might indicate that participants were not attending to the stimuli. However, a correlation analysis between this task and the test phase indicated that the two were not related ($r$ = .08, $p$ = .455) and therefore all subjects were considered for further analysis.

In order to evaluate if the participants learn the statistical regularities during the S*tatistical Learning Test*, the percentage of triplets correctly identified was calculated (mean ± SD = 55% ± 15). A one-sample $t$-test demonstrated that this performance was significantly better than chance (50%; $t(84) = 3.31$, $p < .001$, $d = 0.36$). Nevertheless, these results were lower than expected for adult participants (Arciuli & Simpson, 2012b), so we further analyzed the statistical learning performance . We observed a trend toward a lower performance as the task progressed. We speculate that this was due to the exposure to new triplets during the test – participants might start to assume that a repeated new triplet was actually correct and started to classify new triplets as previously seen triplets. To control for this confound, we decided to consider only the first half of the statistical learning test. Therefore, the percentage of triplets correctly identified was recalculated (mean ± SD = 57% ± 13) and a one-sample *t*-test confirmed that this performance was significantly better than chance (50%; $t(84) = 5.34$, $p < .001$, $d = 0.58$). Furthermore, when asked after the exposure phase if they notice any set of "monsters" that accompanied each other, the majority of the participants indicated that they were not aware of this and the ones that noticed some connections between the "monsters" were not able to reproduce a whole triplet.

In the *Implicit Orthographic Knowledge Decision task*, total scores were converted into percentage (mean ± SD = 63% ± 10) and a one-sample *t*-test was performed to test whether this performance was significantly better than chance (50%). Results show that participants opted for the most frequent orthographic representation ($t(84) = 12.22$, $p < .001$, $d = 1.33$). A correlation analysis of this task with the statistical learning task revealed that both tasks are significantly correlated ($r = .26$, $p = .016$).

Regarding the *Dictation of Pseudowords* task, a significant amount of errors was produced, since participants often wrote variations of the pseudowords presented. Only the well-written pseudowords were counted and the total score was converted into percentage. Results show a mean of 70% (± SD = 8) and a one-sample t-test confirmed that participants opted for the most frequent orthographic representation (50%; $t(84) = 22.24$, $p < .001$, $d = 2.41$). No correlation was found between the dictation of pseudowords and the statistical learning task ($r = -.04$, $p = .748$). Still, both implicit orthographic knowledge tasks were significantly correlated ($r = .23$, $p = .038$).

In the *Reading task*, participants showed a mean of 2.0 (± SD = .3) correctly read words per second and a mean of 1.45 (± SD = .31) correctly read pseudowords per second. Results showed a significant correlation between the statistical learning task and the performance on the overall reading task ($r = .35$, $p = .001$). Specifically, we observed a correlation between the statistical learning task and the number of correct words ($r = .37$, $p < .001$) and pseudowords ($r = .26$, $p = .017$).

**Table 3.1.** Hierarchical multiple regression analysis of the reading and implicit orthographical knowledge tasks as a dependent factors.

| | Step 1 | | | Step 2 | | | |
|---|---|---|---|---|---|---|---|
| | βExp | βSL | $R^2$ | βExp | βSL | βExp*SL | $\Delta R^2$ |
| **Reading** | | | | | | | |
| Present print exposure | .05 | .33* | .11** | -.01 | .33* | -.10 | .01 |
| Past print exposure | .15 | .30* | .13* | .03 | .23** | .28** | .06** |
| **Implicit orthographic knowledge** | | | | | | | |
| Present print exposure | -.05 | .21 | .05 | -.12 | .21 | -.11 | .01 |
| Past print exposure | .05 | .21 | .05 | .09 | .23 | -.08 | .01 |
| **Dictation of pseudowords** | | | | | | | |
| Present print exposure | .01 | -.05 | .00 | .15 | -.05 | .23 | .03 |
| Past print exposure | -.03 | -.05 | .00 | .05 | .00 | -.19 | .03 |

*Note:* βExp = Exposure; βSL = Statistical Learning; βExp*SL = interaction Exp and SL; $R^2$ = variance explained by Exp and SL; $\Delta R^2$ = increment of variance explained by the interaction. * $p < .01$; ** $p < .05$.

Two composite measures were created from the responses to the *Reading Habits Questionnaire*, one regarding the present exposure to print, and the other regarding past exposure to print. Past exposure correlated with word reading ($r = .25$, $p = .028$), but not with implicit orthographic knowledge tasks ($p > .4$). Present exposure did not correlate with the literacy measures ($p > .4$). We tested for the moderating effects of statistical learning on the association between exposure to print and literacy skills (reading and orthographical knowledge) following the Baron and Kenny (1986) procedure (see Table 3.1). In the first step, print exposure and statistical learning entered as predictors in three regression models with reading, implicit orthographical knowledge and dictation of pseudowords tasks as dependent variables. In a second step, the interaction term between print exposure and statistical learning was introduced in the models. The association between present exposition to print and literacy measures was always non-significant (*p*s > .32) and statistical learning does not show any moderator role. However, we found that statistical learning significantly moderates the influence of past exposure to print in reading skills: the interaction term added a significant contribution to the reading score variance ($\Delta R^2 = .06$, $p = .028$); the coefficient of this interaction term is positive (b = 5.97, $\beta = .28$, $t(75) = 2.25$, $p = .028$), indicating that the positive influence of past exposition to print to reading performance is amplified in the presence of good statistical learning capacity. Statistical learning had no moderator effect on the contribution of past exposition to print to other literacy measures.

## DISCUSSION

Overall, there is evidence that suggests that children benefit from implicit learning mechanisms to extract the written language regularities to become skilled readers and spellers. In this study, we investigated the relationship between statistical learning, reading and implicit orthographic knowledge in typical adult readers. We employed a statistical learning task used in previous studies (Arciuli & Simpson, 2011, 2012b) and observed that participants were able to distinguish between correct and incorrect triplets significantly better than chance. This effect occurred despite the fast presentation rate in the exposure phase, the fact that during this phase participants looked at a stream of stimuli without any indication that they were structured, and despite the presentation of unfamiliar stimuli difficult to verbally label. Moreover, participants were unaware of the existence of the triplets after the exposure phase. Thus, evidence suggests that participants learned the statistical pattern they were exposed to implicitly. Nevertheless, the performance was lower than expected. Siegelman, Bogaerts, and Frost (2017) suggest that an extensive repetition of incorrect targets throughout the test phase might induce a progressive acceptance of the incorrect stimuli. In these situations, the score obtained might reflect learning of the exposure phase or memory of the new triplets presented during the test phase. This might have been the case in our task, since we observed a significant decrease in performance from the first to the second half of the test phase, reflecting an increased acceptance of the repeated incorrect triplets. We therefore only analyzed the first half of the task, ensuring less exposure to incorrect triplets, while preserving reliability (Siegelman, Bogaerts, & Frost, 2017).

Implicit orthographic knowledge was assessed with a forced-choice and a pseudoword dictation task. In both tasks, participants performed above chance, that is, they chose or spelled the pseudoword with the most frequent orthographic pattern, although they did not know why they chose that pattern, suggesting that this knowledge was implicit. While both tasks correlated with each other, their relationship with the statistical learning task differed, as we observed a correlation with the forced-choice task but not in the pseudoword dictation task. In the dictation of pseudowords, participants need to produce the orthographic patterns that represent the uttered phonological patterns. On the other hand, to perform the force-choice task, participants do not need to generate the pronunciations and may therefore rely entirely on their orthographic knowledge. Thus, the stronger correlation between the statistical learning task and the forced-choice task might be because both tasks rely on visual patterns more strongly. Therefore, although statistical learning seems to contribute for learning orthographic patterns, phonological patterns and the link between both, this influence seems to occur in different ways (Treiman & Wolter, 2018).

This study replicates the findings of Arciuli and Simpson (2012), the significant correlation between reading and statistical learning. Participants that extracted the regularities present in the statistical learning task better are also more fluent readers. This observed correlation was found not only in word reading, but also in pseudoword reading. These results support the suggestion that the grapheme-phoneme correspondence, although taught explicitly, might be reinforced and benefit from statistical learning mechanisms during acquisition. On the other hand, the results also suggest that an individual that is better at extracting environmental regularities will also be more sensitive to regularities present in text and speech, such as co-occurrence of letters and lexical stress, facilitating reading fluency (Arciuli, 2018).

The reading and statistical learning relationship found is not in line with the suggestion by Nigro, Jiménez-Fernández, Simpson, and Defior (2015) that implicit learning would not be related to reading in relatively transparent orthography. A few explanations for the different results between our study and Nigro and collaborators (2015) study can be advanced: the Spanish orthography is more transparent than the Portuguese and thus statistical learning might play a greater role in reading Portuguese. In Spanish, reading can be accomplished by grapheme-to-phoneme conversions that are explicitly taught and thus statistical learning would play a limited role. In contrast, reading proficiency in Portuguese might benefit from the implicit extraction of regularities that are not covered in formal instruction. Additionally, it might be the case that in the study of Nigro et al. (2015) the correlation was absent due to the age of the participants: they tested 8- and 9-years old children while we tested adults – 8- and 9-years old children are still acquiring reading competences and their exposure to text is necessarily limited compare to adults, therefore providing less opportunities to extract regularities. Overall, these results indicate that the transparency/opacity of an alphabetic written language might modulate how much the acquisition of reading and writing skills can benefit from implicit learning. A cross-linguistic study would help to clarify this issue.

Furthermore, we assessed the reading habits of the participants to have an indirect measure of participants' exposure to text and to evaluate its impact on the literacy measures used in our study. The results show that past exposure to print influenced word reading. Interestingly, this influence was moderated by statistical learning skills. It has been suggested that orthographic knowledge accumulates in early childhood (Steffler, 2001) and that adults do not extract the details of spelling during reading because they pay more attention to the ideas being conveyed (Treiman, 2018). This suggests an explanation for the past exposure to print effect on reading. Exposure to print had no significant impact on the implicit orthographic knowledge, although a more reliable retrospective measure and a larger sample would be useful to assess the impact of previous exposure to text on literacy measures. Nevertheless, it is clear that statistical learning has a role in boosting the impact of print exposure on reading.

In conclusion, this study provides further evidence that statistical learning is associated with implicit orthographical knowledge and reading. Although individuals are largely unaware of the different frequencies of orthographic patterns, they still show knowledge of these frequencies and use them. Exposure to text seems to be one of the most valuable contributions to reading performance.

**This study is under review in:**

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# CHAPTER FOUR

## STUDY 3 - Implicit sequence learning is preserved in dyslexic children


### ABSTRACT

This study investigates the implicit sequence learning abilities of dyslexic children using an artificial grammar learning task with an extended exposure period. Twenty children with developmental dyslexia participated in the study and were matched with two control groups – one matched for age and other for reading skills. During three days all participants performed an acquisition task, where they were exposed to colored geometrical forms sequences with an underlying grammatical structure. On the last day, after the acquisition task, participants were tested in a grammaticality classification task. Implicit sequence learning was present in dyslexic children, as well as in both control groups, and no differences between groups were observed. These results suggest that implicit learning deficits per se cannot explain the characteristic reading difficulties of the dyslexics.

## INTRODUCTION

Developmental dyslexia (henceforth, dyslexia) is the most common learning disorder and it is characterized by severe and persistent difficulties in learning how to read, despite normal intelligence, adequate cognitive abilities, and appropriate instruction (Lyon et al., 2003; Tunmer & Greaney, 2011; Vellutino et al., 2004). A vast number of studies have identified a phonological processing difficulty as a core feature of dyslexia, specifically, underspecified or/and less accessible phonetic representations in these readers (e.g., Boets et al., 2013; Ramus et al., 2003). Indeed, individuals with dyslexia have been shown to perform below average on a range of tasks that require phonological processing skills (e.g., phonological awareness, phonological decoding, rapid automatized naming and verbal short-term memory) (Ramus et al., 2003; S. Shaywitz, 2003; Tijms, 2004; Wagner et al., 1994). In addition, dyslexia disorder has been linked to non-linguistic processing deficits, including visual and auditory processing (Sela, 2014), visual spatial attention (Franceschini et al., 2012), and, discussed more recently, to implicit learning (for a review, see Folia et al., 2008; Lum, Ullman, & Conti-Ramsden, 2013; Schmalz, Altoè, & Mulatti, 2016; van Witteloostuijn, Boersma, Wijnen, & Rispens, 2017). The term implicit learning was introduced by Reber (1967) and refers to a type of unintentional learning that results from constant exposure to environmental regularities, without awareness of what has been learned. This process is not voluntary mediated, yet it is still controversial to what extend implicit learning drives abstract and unconscious knowledge (Cleeremans et al., 1998).

A crucial phase during the development of reading abilities is to learn and automatize the associations between letters and sounds. Fluent reading will benefit from the extraction of regularities from visual and auditory sequences (e.g., co-occurring letters), important for the formation of letter and word representations (Ehri, 2005). This occurs through both explicit and implicit learning processes: the former takes place throughout formal instruction and the last merely through exposure to text (Stoodley & Stein, 2011b). Hence, impaired reading in dyslexia may be related to a deficit in implicit learning. A few plausible mechanisms have been suggested to explain how a weakness in implicit learning of sequential information could account for the phonological processing and reading problems in dyslexia. The cerebellar deficit hypothesis of dyslexia (Nicolson & Fawcett, 1999; Nicolson et al., 2001) claims that children with dyslexia have unusual difficulty in automatizing any skill, whether motor or cognitive. Because implicit learning has been closely linked with automatic learning mechanisms (Conway & Pisoni, 2008) it may well be that an implicit learning deficit would affect learning of grapheme-phoneme associations in children with dyslexia and eventually prevent them from reaching a high degree of automaticity in reading (Sperling et al., 2004). Howard, Howard, Japikse, & Eden (2006) also suggest that poor implicit learning could hinder the establishment of adequate phonological processing as well as learning orthographic-phonological representations. The authors propose that a combination of a phonological deficit with an impaired sequence learning system could manifest as a failure in applying implicit or probabilistic rules required for fluent application of grapheme-phoneme correspondences and, therefore, leading to reading difficulties (see also Sperling et al., 2004).

The capacity of implicit learning of dyslexics has been tested in a number of studies, however with contradictory results. Some studies have found that dyslexic readers have an implicit learning deficit, especially when the task has a strong sequencing component (Kahta & Schiff, 2016; Deny Menghini et al., 2006; Stoodley et al., 2006; Stefano Vicari et al., 2003), and a correlation between implicit learning and individuals' reading ability as been reported (Sperling et al., 2004). Other studies, however, have found null results, i.e., implicit learning abilities were apparently intact both in children and adults with dyslexia when compared to typical readers (e.g. Kelly, Griffiths, & Frith, 2002; Nigro, Jiménez-Fernández, Simpson, & Defior, 2016; Roodenrys & Dunn, 2008). Furthermore, Waber and collaborators (2003) have found no evidence that reading ability is associated with implicit sequential learning.

Factors that varied between studies may explain the apparent discrepancies, including the tasks used to assess implicit learning (Howard et al., 2006; Roodenrys & Dunn, 2008). For example, studies that employed two different implicit learning tasks (Howard et al., 2006; Jiménez-Fernández et al., 2010) found evidence for a deficit on the serial reaction time tasks in dyslexics compared with typical readers, while there were no differences between these groups on other implicit learning tasks, such as the spatial context learning task. Additionally, when we look in to the studies with dyslexics that employed another implicit learning task, the artificial grammar learning paradigm, we also find contradictory results (Laasonen et al., 2014; Pavlidou et al., 2010; Pothos & Kirk, 2004; Rüsseler et al., 2006). Artificial grammar learning (AGL) tasks differ from the SRT tasks in the sense that they require less involvement of the motor system and represent a more complex and abstract implicit learning situation. Consequently, both tasks are thought to reflect different cognitive and neural processes (Laasonen et al., 2014). However, a closer look into these discrepant results presented by studies with dyslexics using the AGL task will show an important difference between them: the participants' age. While some studies with dyslexic children reported poor performance in implicit learning (Pavlidou et al., 2010, 2009), others show that dyslexic adults even outer perform the typical readers (Pothos & Kirk, 2004). Russeler, Gerth and Munte (2006) studied the implicit learning abilities of dyslexic adults using both AGL and SRT paradigms and observed that these individuals were unimpaired in both tasks. Laasonen and collaborators (2014), in turn, found no major differences between dyslexic adults and typical readers in the SRT task, only in the AGL task. In this study, there was a non-significant main effect of group, but while in control readers the grammaticality accuracy was above chance levels, in the dyslexic readers performance did not exceeded the chance level. The authors suggested that these findings could be explained by the shorter presentation time and the reduced number of items used in the learning phase that might have hampered dyslexics' performance. Overall, studies using the AGL paradigm with dyslexic children report poor implicit learning, but this deficit is probably mitigated in dyslexic adult samples. Nevertheless, it is not clear whether the poorer results presented by dyslexic children are due to participants' characteristics beyond age or to the AGL task characteristics, such as short exposure periods.

In sum, there is considerable debate on whether implicit learning is affected and contributes to impaired reading in dyslexia. In the present study we aim to further investigate the implicit sequence learning abilities in dyslexic children, using an AGL task that was designed to minimize factors that might prevent implicit learning from occurring (such as slower performance) and, importantly, to maximize the exposure to the sequence regularities. For this, we used an extended acquisition phase (three days), unlike prior studies. This is important because consolidation promoted by sleep fosters optimal performance in implicit learning (Nieuwenhuis et al., 2013). Another novelty of this study is that we compared the performance of dyslexic children with that of a control group matched for chronological age and a control group matched by reading level. The lack of such a reading-matched control group is an important gap in the previous studies, as its inclusion allows us to exclude that a given deficit is simply a consequence of the less reading experience in dyslexic children. If dyslexic children do have an implicit learning deficit, one would expect them to perform more poorly on the AGL task even when compared with the reading-matched controls, indicating therefore a disrupted implicit learning ability in this population.

## METHODS AND MATERIALS

### PARTICIPANTS

All participants were children recruited from Portuguese elementary schools (2nd – 4th grade), with normal or corrected to normal vision. Informed consent was obtained from their parents. Twenty children (12 male and 8 female, mean age ± SD = 9.5 ± 1.1 years; mean grade ± SD = 3.1 ± 0.9) with either a formal dyslexia diagnosis or a suspicion of dyslexia (as indicated by their teachers) were further assessed in order to confirm if they met all the inclusion criteria. The inclusion criteria for the dyslexia group were: 1) absence of neurological or emotional problems (including ADHD); 2) normal range non-verbal IQ as measured by the Raven Coloured Matrices (Raven, Raven, & Court, 2009); 3) reading abilities significantly below grade mean level in the reading and spelling subtests (i.e., either a reading speed score ≥ 1.25 SD below the grade mean or a reading speed score ≥ 0.75 SD below the grade mean combined with a spellings score ≥ 1.25 SD below the grade mean) of the Differential Diagnosis Dyslexia Battery of Maastricht-3DM (Blomert & Vaessen, 2009; A. Pacheco et al., 2014); 4) reading scores below the 25th percentile on a reading comprehension test (Teste de Idade de Leitura - TIL; Santos & Castro, 2010).

Two control groups were selected to match the dyslexic group: one group matched for age (age-matched control) and other matched for reading skills (reading-matched control). For the age-matched control group, twenty children (12 male and 8 female, mean age ± SD = 9.1 ± 0.6 years; mean grade ± SD = 3.5 ± 0.8) classified by their teachers as average pupils were selected. For the reading-matched control group, twenty children (12 male and 8 female, mean age ± SD = 7.1 ± 0.4 years; mean grade ± SD = 1.4 ± 0.5) were selected from the same schools as the other children. At the time of testing these children were at the end of the first grade or beginning of second grade and were already able to read (they were all classified by their teachers as average or above average pupils). Specific inclusion criteria for the control groups were: 1) absence of neurological or emotional problems (including ADHD); 2) normal range non-verbal IQ as measured by the Raven Coloured Matrices; 3) reading abilities within or above the grade mean level in the 3DM reading and spelling tests; and 4) reading scores above the 25th percentile in TIL.

**TABLE 4.1.** Group performance on the reading, spelling, phonological awareness, rapid automatized naming, vocabulary and phonological short-term memory tasks (mean ± SD). Raw scores were used in all tasks (Note that the reading-matched control group performance is adequate for their age when values are converted to standardized scores).

| | **Dyslexic group (n = 20)** | **Age-matched control group (n = 20)** | **Reading-matched control group (n = 20)** |
|---|---|---|---|
| Word reading (word/sec) | 0.35 ± 0.18 | 1.27 ± 0.29* | 0.45 ± 0.13 |
| Spelling (%) | 65.16 ± 12.89 | 85,86 ± 6.00* | 72.39 ± 11.27 |
| Phoneme deletion (%) | 33.04 ± 21.20 | 79.96 ± 13.74* | 49.89 ± 27.74* |
| Rapid naming (item/sec) | 1.14 ± 0.22 | 1.76 ± 0.24* | 1.27 ± 0.19 |
| Vocabulary (score) | 16.00 ± 3.93 | 19.75 ± 5.06* | 14.15 ± 2.74 |
| Digit span (score) | 8.00 ± 1.81 | 10.80 ± 1.80* | 9.10 ± 1.94 |

* = mean scores significantly different from dyslexic group mean scores (*p*'s < .05).

A t-test for independent samples confirmed that the reading and spelling scores of the dyslexic group were significantly lower compared with those of the age-matched control group (both p's < .01), but not compared with the reading-matched control group (p = .26, for reading and p = .08, for spelling). The dyslexic and the age-matched control group did not differ from each other in terms of age and years of education (p = .24 and p = .30, respectively), and both groups were significantly older and from a higher grade than the reading-matched control group (both p's < .01). Additionally all groups were initially tested on phonological awareness, rapid automatized naming [subtests selected from the 3DM battery (A. Pacheco et al., 2014)], vocabulary and phonological short-term memory [from the Wechsler Intelligence Scale for Children (Wechsler, 2006)]. The dyslexic group showed significantly lower scores compared with both control groups in all tasks (table 4.1). No differences emerged between the two control groups when raw values were converted into standardized values (all p's ≥ .37).

STIMULUS MATERIAL

Using a regular grammar defined by the finite-state generator described in Figure 4.1, we generated the complete set of grammatical (G) stimulus sequences with a length of 4 to 7 elements from a symbol alphabet with coloured geometrical forms (green triangle, yellow square, red circle, blue diamond; see Figure 4.1). The coloured geometrical forms were used instead of orthographic material in order to facilitate acquisition by all children and to not benefit those without dyslexia. The stimulus material includes one acquisition set and one classification set. In order to quantify differences in subsequence familiarity between acquisition and classification items, associative chunk strength (ACS) was calculated for each sequence. The ACS captures the frequency distribution of 2- and 3-letters chunks for the complete sequence positions (Knowlton & Squire, 1996; Meulemans & Linden, 1997). Of the total set of grammatical sequences, 36 items were selected for the acquisition set using an iterative random procedure. This procedure guaranteed that the acquisition set was comparable in terms of ACS familiarity to the complete set. Non-grammatical (NG) items were generated by switching two geometrical forms in non-terminal positions from each remaining grammatical items, keeping the ACS score balanced with its original template item (see appendix 3). For the classification set, 20 grammatical and 20 non-grammatical pairs were selected from the remaining items in an iterative random procedure, while ensuring that 10 items were equivalent in ACS to the acquisition set and the remaining 10 items showed a significantly lower ACS score. In this way, the classification set was organized in a 2x2 factorial design, with grammaticality (grammatical/non-grammatical) and ACS (high/low) as factors, including 10 sequences of each category: high ACS grammatical (HG), low ACS grammatical (LG), high ACS non-grammatical (HNG), and low ACS non-grammatical (LNG).

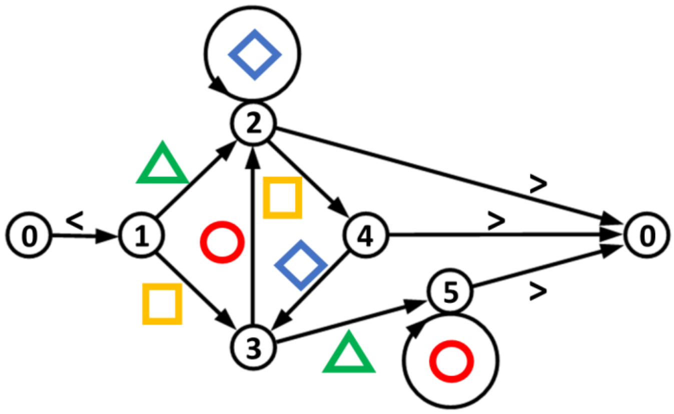


**FIGURE 4.1.** The transition graph representation of the regular grammar used in the present study. Sequences that follow the transitions in this graph are grammatical while sequences that do not are not. An example of a grammatical sequence would be "square-circle-square-diamond-triangle" and a non-grammatical sequence would be "square-circle-diamond-circle-square".

PROCEDURE

All sessions were conducted in the schools of the children, in a quiet and undisturbed room. First, reading and cognitive assessment was performed in order to select our participants. Afterwards, participants performed the AGL experiment, divided in three sessions conducted over three consecutive days. All tasks were presented visually on a computer screen and responses were recorded using a Cedrus RB series response pad, connected to the laptop. All sessions started with a short-term memory cover task, the acquisition task. During this task, participants were exposed to and had to memorize grammatical sequences, which remained on the screen for 8 seconds each. After that, participants were asked to reproduce the sequence, in a self-paced manner, using the response pad to type the coloured geometrical forms (one button per geometrical form). The sequences presentation order was randomized for each acquisition session and each session lasted for approximately 20 minutes. After the acquisition task, participants were interviewed in order to assess the level of experienced difficulties in fulfilling this task.

On the third day, after the short-term memory task, participants engaged in an intermediate irrelevant task, in order to divert attention from the acquisition task. In this task, subjects had to press one of four buttons whenever they saw a frog in one of four matching positions of the computer screen. Subsequently, the participants' knowledge about the underlying grammatical structure was tested using a grammaticality classification test. The participants were informed about the existence of a complex set of rules that underlies the acquisition sequences structure and were instructed to classify new sequences (20 grammatical and 20 non-grammatical) in sequences that followed those rules and sequences that did not comply with those rules (i.e., grammatical or non-grammatical). Each sequence was presented on the screen for 3 seconds followed by a grammaticality judgement (forced yes/no choice). The participants were instructed to base their decision on their immediate intuition and to avoid any attempt to explicitly analyse the sequences. The presentation order was randomized and the classification test lasted for approximately 10 minutes. The session finished with an interview in order to assess their explicit knowledge about any pattern or rule system.

## RESULTS

### ACQUISITION TASK

The accuracy in the acquisition task was analysed with a repeated-measures ANOVA with the group as between-subject factor (dyslexics/age-matched controls/reading-matched controls) and the acquisition days as within-subject factor (day 1/day 2/day 3). The results showed a large main effect of group [$F$ (2, 57) = 14.78, $p$ < .001; partial η2 = .34]. A post-hoc analysis (Tukey HSD) revealed that age-matched controls performed more accurately (percentage mean ± SD = 57.46 ± 7.20) than the dyslexic (percentage mean ± SD = 40.69 ± 4.19; *Cohen's d* = 2.85) and reading-matched control groups (percentage mean ± SD = 36.88 ± 5.15; *Cohen's d* = 3.29) (all *p*'s < .001). The performance of the dyslexics and reading-matched controls did not significantly differ from each other ($p$ = .61; *Cohen's d* = 0.81). A large main effect of acquisition day was also observed [$F$ (2, 114) = 55.12, $p$ < .001; partial η2 = .49], revealing an increase in performance over the three days (all *p*'s < .001). There was no significant interaction between the factors acquisition day and group [$F$ (4, 114) =1.98, p = .10; partial η2 = .07].

### CLASSIFICATION PERFORMANCE: ENDORSMENT RATES

The classification performance was analysed in terms of endorsement rate (i. e., an item classified as grammatical independent of the real grammaticality status of the sequence, cf. Meulemans & Linden, 1997). Both grammaticality and ACS status influenced the endorsement rate (Figure 4.2 and Figure 4.3). A repeated-measures ANOVA with grammaticality (G/NG) and ACS (High - H/Low - L) as within-subject factors and group as a between-subject factor (dyslexics/age-matched controls/reading-matched controls) showed a large main effect of grammaticality [$F$ (1, 57) = 23.74, $p$ < .001; partial η2 = .29], because the endorsement rate was higher for grammatical than for non-grammatical sequences (percentage mean ± SD = 52.88 ± 2.10 and 39.36 ± 2.50, respectively), and a main effect of ACS [$F$ (1, 57) = 50.93, $p$ < .001; partial η2 = .47], because the endorsement rate was higher for high compared to low ACS sequences (percentage mean ± SD = 53.53 ± 2.08 and 38.71 ± 2.15, respectively). The interaction between grammaticality and ACS [$F$ (1, 57) = 18.00, $p$ < .001; partial η2 = .24] was also significant. A *post-hoc* analysis revealed that there is an ACS effect only in the grammatical sequences: endorsement rates were significantly superior for high ACS grammatical sequences (percentage mean ± SD = 64.33 ± 18.61) versus low ACS grammatical sequences (percentage mean ± SD = 41.43 ± 19.75; p < .001). Although the performance on high ACS non-grammatical sequences (percentage mean ± SD = 42.72 ± 24.22) was higher than that on low ACS non-grammatical sequences (percentage mean ± SD = 36.00 ± 19.76), this difference was only near significance ($p$ = .07).

Importantly, there was no main effect of group [$F$ (2, 57) = .10, $p$ = .903; partial η2 = .004]. Furthermore, neither the effect of grammaticality nor of ACS interacted with the factor group, as indicated by the non-significant two-way interactions (group by grammaticality: $F\ (2, 57) = .18$, $p = .83$; partial η2 = .01; group by ACS: $F\ (2, 57) = .78$, $p = .46$; partial η2 = .03) and the non-significant three-way interaction [$F\ (2, 57) = .49$, $p = .62$, partial η2 = .017].

In addition to the endorsement rate analysis, we performed further a response time analysis as, despite unimpaired accuracy performance, dyslexics showed slower response times which could reflect different cognitive processes when dealing with the task (see, for example, Kelly et al., 2002). However, we find no significant differences between groups or conditions in the response times (all $p$'s ≥ .08).

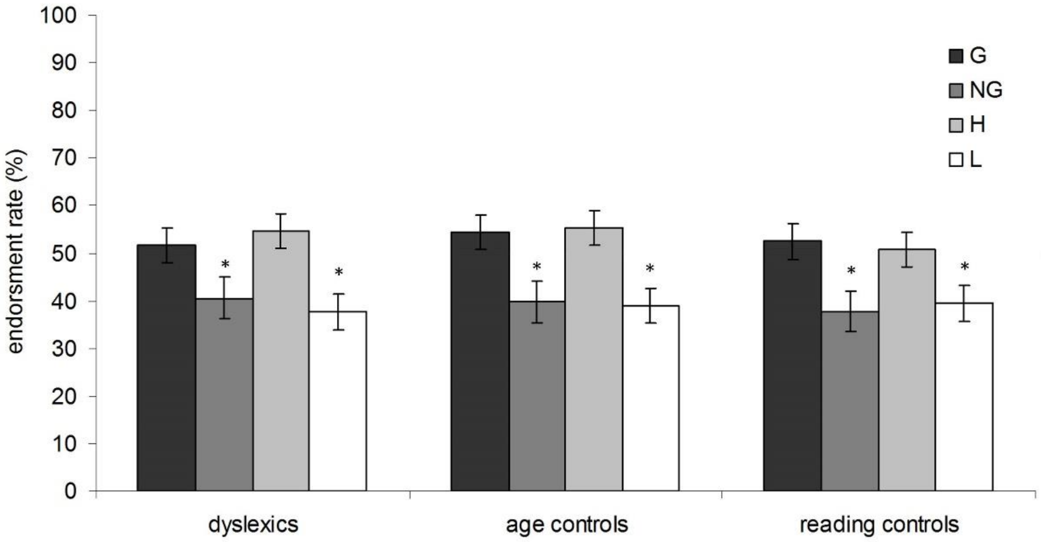


**FIGURE 4.2.** Endorsement rates over grammaticality and ACS as main factor categories. (G: Grammatical sequences; NG: Non-Grammatical sequences; H: High ACS sequences; L: Low ACS sequences). Error bars correspond to standard error of the mean. * = average endorsement rate is significantly different from chance (T-test, $p < .05$).

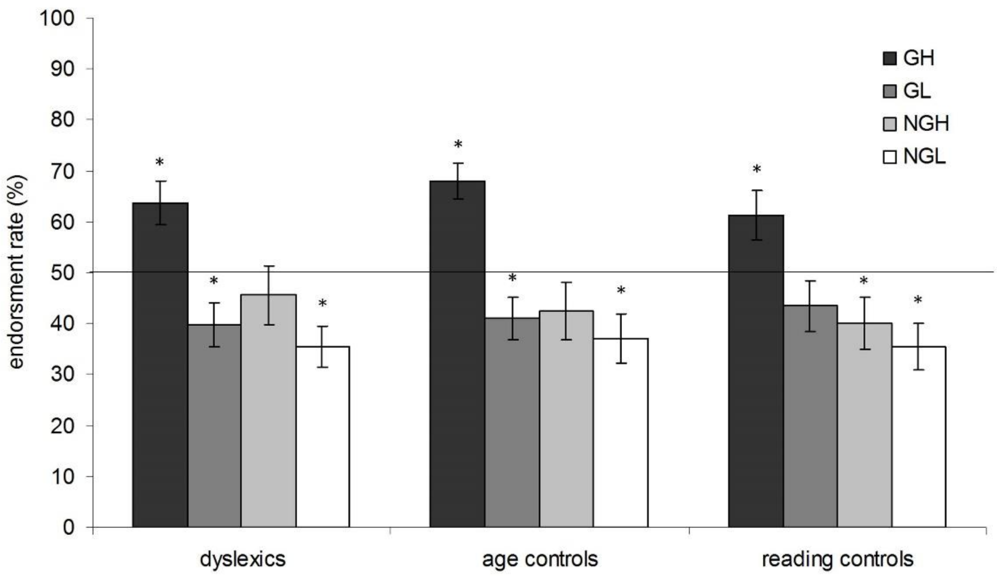


**FIGURE 4.3.** Endorsement rates over grammaticality and ACS levels (GH: Grammatical High ACS sequences; GL: Grammatical Low ACS sequences; NGH: Non-Grammatical High ACS sequences; NGL: Non-Grammatical Low ACS sequences). Error bars correspond to standard error of the mean. * = average endorsement rate is significantly different from chance (T-test, $p < .05$).

## INDIVIDUAL ANALYSIS

While we found no differences between groups on the classification task performance, it may be that by performing a group level analysis we have missed relevant individual aspects. Thus, we further used an individual-level approach to investigate performance on the AGL task (Figure 4.4). In this analysis, four dyslexic children performed high above the chance level, indicating that these participants were able to discriminate between grammatical and non-grammatical items. Four participants in the age-matched control group and seven participants in the reading-matched control group were also very good on the classification task, as shown by their *d'* values. Some children presented very high levels of discrimination in the opposite direction (expressed by their strong negative *d'* values), probably because of misinterpretation of the instructions or confusion with the response buttons. We re-analysed the data excluding these participants and no changes were observed in the overall pattern of results.

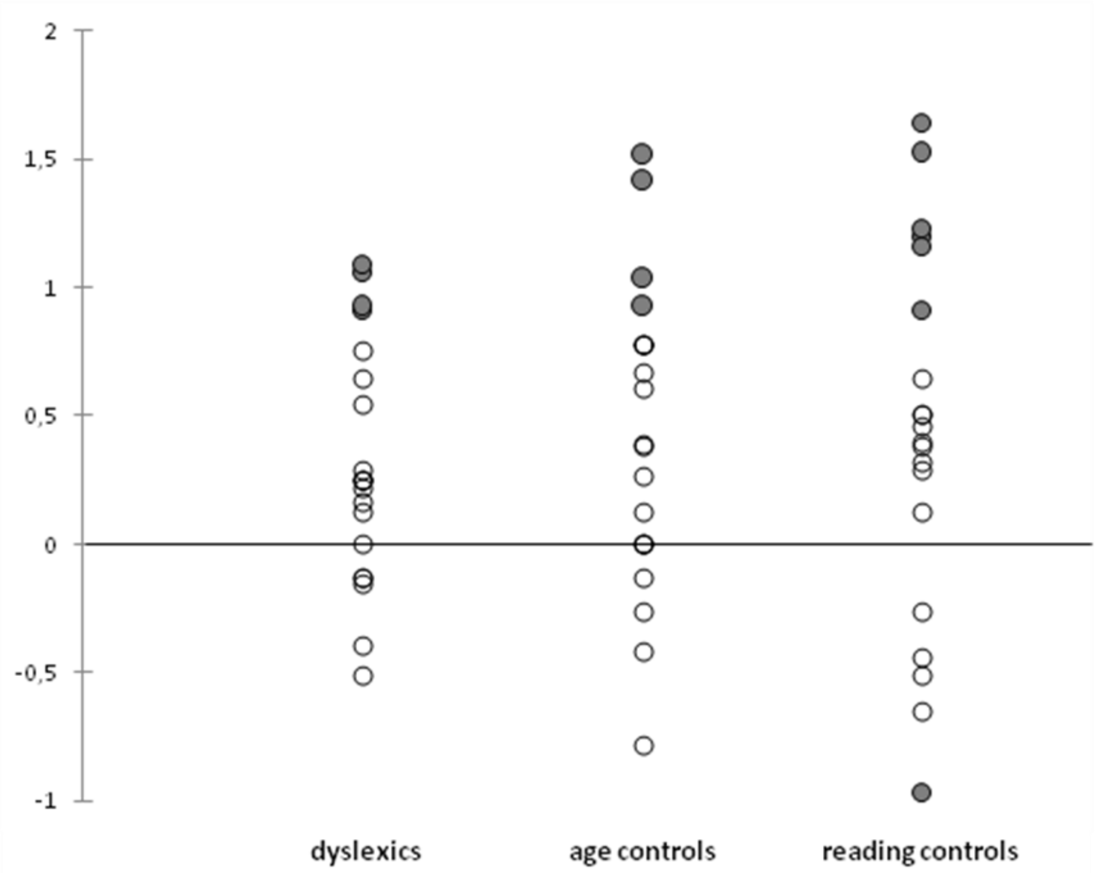


**FIGURE 4.4.** *d'* for grammaticality by participant [age controls = age-matched control group; reading controls = reading-matched control group; filled dots for accuracy level above chance (binomial test $p < .05$, two-tailed)].

EXPLICIT KNOWLEDGE

In order to assess if participants were using or were aware of any rule system underlying the sequences, they were interviewed at the end of the acquisition and classification tasks. After the classification task, the participants were asked to reproduce grammatical sequences using cards with the coloured geometrical forms that they had been previously presented. Participants were aware of a few salient characteristics (namely, all sequences started with triangles or squares and these shapes, contrary to others, were never repeated in a sequence). These salient features were uncovered in the acquisition task for some children, others only reported them after the classification task. Some of the children were able to create grammatical sequences with the cards (maximum of five correct sequences), all corresponding to sequences that they saw in the acquisition task. This ability to generate grammatical sequences did not correlate with the grammatical discrimination index, *d'* ($r$ = .11, $p$ = .39). Therefore, there is evidence of explicit knowledge for the sequences presented in the acquisition task, but there is no evidence of such knowledge for the grammatical rules, since the children could not produce new grammatical sequences or made explicit rules that are more complex. Furthermore, the fragmented explicit knowledge the participants have (i. e. which geometrical forms can be repeated and those used to start the sequences) does not benefit them since all sequences in the classification task – both grammatical and non-grammatical – display those features.

## DISCUSSION

This study aimed to investigate whether dyslexic children can accomplish implicit sequence acquisition in an artificial grammar learning paradigm. In the classification task, new grammatical and non-grammatical sequences were presented and participants were asked to classify them. In this test there were no differences between dyslexic and any of the control groups (age- and reading-matched control), indicating that regardless of their reading status all participants acquired the stimulus regularities at a similar level. The endorsement rates were also influenced by grammaticality likewise: all participants rejected non-grammatical sequences and there was a leaning to accept grammatical sequences.

Regarding the acquisition task, we did observe an effect of group as the age-matched control group performed better than both the dyslexic and the reading-matched control groups (which in turn did not differ from each other). This result is somehow expected as dyslexic children have been shown to present poor short term memory (e.g. Trecy, Steve, & Martine, 2013; or Wang & Gathercole, 2013) and the acquisition task relies strongly on this skill. In reading-matched controls, we do not believe this is the case, their lower performance probably reflect their development stage (Gathercole, Pickering, Ambridge, & Wearing, 2004). Nevertheless, the performance in this task did not mirror the performance in the classification task. It has been already shown that implicit learning is not related with working memory (Kaufman, DeYoung, et al., 2010). Furthermore, a poorer working memory capacity (as dyslexics in our group present - see Table 4.1) did not prevent them from extracting the regularities of the sequences presented in the acquisition task. In line with this results, Conway, Bauernschmidt, Huang, & Pisoni (2010) suggested that even if the ability to encode and hold a series of items in immediate memory is necessary to learn a sequence structure, this ability per se is not sufficient, and a well-functioning mechanism involved in learning the underlying regularities is also needed. Consequently, a reduced memory capacity might actually be beneficial for learning complex input because it can act as a filter to reduce the complexity of the problem space, making it more manageable. The participants' working memory capacity could aid the sequence learning in both directions but through different mechanisms: for the controls, a better working memory helps them to encode and hold the sequence items more efficiently, improving the sequence structure learning. For the dyslexics, a poorer working memory capacity may force them to transform the sequence items into more manageable units that would support the capture of the sequence structure.

For all tested groups the performance in the classification task was below what was expected. Most of our participants, either dyslexic or typical readers, performed at chance level. Specifically, and as Siegelman and collaborators noted (see Siegelman, Bogaerts, Christiansen, & Frost, 2017; Siegelman, Bogaerts, & Frost, 2017), this may have occurred because of the reduced number of trials or the homogeneous level of difficulty across trials in the classification task. The effect sizes observed in the group analysis and the individual participants' performance showed that at least some of the dyslexic children did reach high levels of grammaticality discrimination, like typical readers do. Additionally, the post-experimental interviews and sequence generation task results confirmed that no group in our study acquired explicit knowledge of the underlying grammatical system. Therefore, the overall pattern of results seems to indicate that implicit learning of the artificial grammar is preserved in dyslexic children.

Our results diverge from those obtained by Pavlidou and colleagues, who also tested dyslexic children using an AGL task with similar set of stimuli, but with a different paradigm (Pavlidou et al., 2010, 2009). Their results showed that while dyslexic children were performing at chance levels, the typically developing children were able to successfully distinguish between grammatical and non-grammatical items. From these results the authors suggested that dyslexic children were not as able as typical readers in abstracting implicit knowledge, that is, to extract the regularities of highly complex structured patterns such as AGL (Pavlidou et al., 2010). However, we might argue that in Pavlidou's studies the acquisition process employed did not allow the dyslexic children to extract and/or consolidate the regularities of the sequences. It has already been shown that dyslexic individuals may need different strategies to cope with implicit learning tasks. For example, Kelly and colleagues (2002) and Roodenerys and Dunn (2008) showed that although dyslexics performed at the same level as typical readers in a SRT task, they were slower. In the studies performed by Pavlidou and colleagues (2010, 2009) there was a limited exposure to grammatical items (only one acquisition session followed by an immediate classification test) that might led to a poor consolidation (Nieuwenhuis et al., 2013), probably hampering dyslexics' performance. To our knowledge, the present study was the first to extend the acquisition phase to three days with an AGL task in children with dyslexia. We did not measure the classification performance in the first two days, but still we consider that overnight consolidation processes and extended practice might have enhanced participants' performance for all groups (but see also Hedenius et al., 2013). A longer period of practice and exposure to grammatical sequences would perhaps even increase their classification performance and eliminate the ACS effect observed: the regularity extraction might have been placed into the smaller units due to still weak consolidation processes. On the other hand, the ACS effect might have been enhanced by the instruction given in the acquisition task (memorize and reproduce the grammatical sequences), which emphasizes lower (constituent element) and mid-level knowledge (bigrams) (cf. Pavlidou, 2010). Future studies favoring the consolidation processes with a less demanding load on item memorization might help to unravel if the observation of an impaired performance by dyslexic children in previous AGL studies (Pavlidou et al., 2010, 2009) is due to insufficient exposure to grammatical regularities, and if the ACS effect is due to task demands.

Finally, another aspect that deserves consideration is the focus on group level analysis in prior studies of implicit learning in dyslexia. This kind of analysis may conceal positive individual achievements and one wonder whether there were in these studies at least some dyslexic individuals who have their implicit learning abilities intact. In fact, in the present study and consonant with Stoodley and colleagues (2006), in the individual level analysis we observed that some dyslexics present a high level of discrimination between grammatical and non-grammatical sequences. This finding might reflect the substantial heterogeneity of deficits found in dyslexia (Stoodley et al., 2006). It is also possible that the divergent results in the literature reflect both the variation of tasks used (see, for example, Howard et al., 2006; Jiménez-Fernández et al., 2010; Rüsseler et al., 2006) but also sample characteristics, as studies typically differ in their operational definitions of dyslexia (e.g., cut-off levels for reading and IQ). In our study, we tried to disentangle if those dyslexic children who presented a high performance in the AGL classification had different cognitive characteristics from those who had a worse performance, but we did not find any consistent pattern; therefore, we cannot draw any conclusion on this issue. Future studies using a larger sample of dyslexics, a more detailed assessment of their deficits and including individual level analysis could clarify this question.

In conclusion, the present study showed that dyslexic children are able to extract the implicit regularities of an artificial grammar to a similar degree as typical readers do, at least as long as sufficient consolidation is allowed. Remediation programs are encouraged to exploit this implicit learning ability, trough the promotion of ludic pedagogical activities in which children are incidentally exposed to linguistic regularities (such as orthographic patterns) outside reading and writing tasks. Further research is needed to evaluate the impact of such pedagogical interventions based on implicit learning strategies for dyslexia remediation.

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# CHAPTER FIVE

## GENERAL DISCUSSION - Main results, limitations and future studies

The present dissertation aimed to investigate whether the implicit learning mechanisms could be captured with the eye-tracking measures and whether these mechanisms have an impact on reading and writing processes, both in typical readers and dyslexics.

In the first study, we aimed to explore whether eye-tracking captures the effects associated with the implicit acquired knowledge in artificial grammar learning tasks. With two experiments, in which we manipulated the presence of a concomitant active test, we showed that eye-tracking measures are sufficient to capture implicit knowledge, although the sensitivity of these measures is boosted in the presence of an active forced-choice task. We showed that the eye-tracking signature of the sensitivity effects in artificial grammar learning tasks can be translated into whole-trial (dwell time and number of fixations) eye-tracking responses to the violating event, rather than first-pass measures (first-fixation duration) to the whole sequence.

An issue of importance in this study is if the improved sensitivity of the eye-tracking measures with active tests imply that we are in the presence of explicit knowledge. We consider this not to be the case. In fact, and in line with the behavioural results, we observed that an improved ocular discrimination of grammatical and non-grammatical sequences occurs even when participants perform the active preference test, where there is no disclosure about the presence of a set of rules underlying the presented sequences. Moreover, although some participants could generate grammatical sequences, we are convinced that they were unaware of the grammar and that these sequences were produced, by chance, with memory of chunks, ruling out the hypothesis of explicit knowledge interference. On the other hand, passive tests only required that participants looked into the sequences. This procedure might have lead to a lack of optimal levels of attention, or to the structure analysis of the sequences not being extracted. Is therefore possible that the display of implicit knowledge to be captured by eye-tracking measures was concealed, leading to the need for further studies to clarify this issue.

In the second study, we aimed to assess whether implicit learning was related to literacy skills and to what extent exposure to print could be related to these skills. Specifically, we intended first to establish if there was a trend of using the most frequent orthographic pattern out of two correct and phonologically equal choices. Our results showed that participants chose the most frequent orthographic pattern, either when presented with two choices or when asked to spell a pseudoword and, in both cases, without an explanation for such choice. These results already indicate that the preference for spelling the most frequent orthographic pattern was acquired implicitly by exposure to the regularities of text. However, we went further and analysed whether the implicit orthographic knowledge presented by our participants was related to their performance in an implicit statistical learning task. Unexpectedly, we observed that the statistical learning skills were related to the implicit knowledge of frequent orthographic patterns in the implicit orthographic knowledge decision task, but not to the dictation of pseudowords. This difference in the correlations between the implicit orthographical knowledge tasks and the statistical learning task might be merely due to the nature of the presented tasks, which require different cognitive processes. To perform the statistical learning and the implicit orthographic decision tasks, one can rely only on the visual patterns, while in the dictation of pseudowords task, we need to convert the phonologically uttered patterns into orthographic patterns, necessarily implying other resources than merely visual. It seems, then, that implicit learning contributes in dissimilar ways to the acquisition of orthographic patterns, phonological patterns and the link between both, but further studies are necessary to explore the details of this differentiated contribution.

The second goal of this study was to test the hypothesis that implicit learning could have less importance for reading competence in orthographies more transparent than English (Nigro et al., 2015). Although not being transparent, the Portuguese orthography is less opaque than English's, and thus, correlations should be weaker or null. Our results showed that this is not the case, as a moderate correlation between the reading and the statistical learning tasks emerged, similarly to the original study, with

English-speaking participants (Arciuli & Simpson, 2012b). It seems, then, that participants that better extract the environmental regularities use these abilities to extract the regularities present in print, becoming better readers. These results were further supported by the moderator role that we found for statistical learning in the influence of exposure to print on reading competence. Statistical learning abilities appear to bolster the role of print exposure for reading proficiency. However, we did not find similar results for the other literacy measures related to orthographic knowledge. It would be interesting if a more comprehensive study, with more participants and more detailed measures of exposure to print, could highlight the role of the reinforcement that implicit learning has in the literacy measures other than reading.

Following this second study, where we observed an association between literacy competence and implicit learning abilities, we aimed to test, in the third study, whether an implicit learning deficit could be an underlying cause for the reading difficulties presented by dyslexic children. This study provided evidence that dyslexics perform as well as typical readers (both matched by age and by reading level) in an artificial grammar learning task. Furthermore, the individual analysis of participants' performance clearly showed that in each group (including the dyslexic group) there were participants that showed very high levels of discrimination between grammatical and non-grammatical sequences, suggesting that an implicit learning deficit does not prevent dyslexics from extracting the regularities present in the orthography. From this study, we can, however, acknowledge that the dyslexics' implicit acquisition processes might be different from the typical readers' processes. This hypothesis can be inferred because although dyslexics performed poorly in the acquisition phase, compared to the typical readers matched by age, they were still as able as the former group to implicitly extract the underlying structure of the presented grammar and thus perform at the same level as the control group in the acquisition phase. Furthermore, we showed that with an extended period of exposure to the grammatical regularities (in this case, three sessions in consecutive days) dyslexics can successfully learn an implicit artificial grammar task, as opposed to previous studies, with only one exposure session (as in Pavlidou, Kelly, & Williams, 2010; Pavlidou, Williams, & Kelly, 2009 studies). Further studies would help to clarify whether the implicit regularity extraction occurs through different processes by manipulating the amount of exposure or assessing this implicit knowledge with methods beyond the behavioural measures, such as eye-tracking measures.

In studies 1 and 3, we opted to study the implicit learning mechanisms, employing a core experimental tool for the study of the implicit learning phenomenon: the artificial grammar learning paradigm. This paradigm is thought to require less involvement of the motor system and represents a more complex and abstract implicit learning situation than other implicit learning paradigms. However, we obtained unexpected results in study 3, with all groups performing below what was expected (e.g. Folia et al., 2008; Folia, Uddén, Forkstam, & Petersson, 2010). Although the designed task allowed some dyslexics (and some typical readers) to apprehend the grammar implicitly, the mean results were not so robust, being only slightly above chance level. In order to be more child-friendly, we opted to shorten the exposure phase (in relation to study 1) to three sessions, which might have led to insufficient consolidation processes (Nieuwenhuis et al., 2013). An additional confounding factor that could have lowered the children's performance was the copy procedure in the acquisition phase. This was a cover task designed to expose participants to the implicit grammar that required that participants copied a previously presented sequence, by memory, without performance feedback. This procedure, however, might have led to the production of errors in the copied sequences, leading to the acquisition of the error or to no acquisition at all (as, in fact, some participants of all groups demonstrated). To strengthen the results presented in study 3, further studies could benefit from an acquisition phase that eliminated the aforementioned confounding factor (providing, for example, the sequence to be copied while the copy was made), on the one hand, and also providing a more extensive period of exposure, on the other, eventually leading to an overall better performance of all groups. A similar confounding factor could have arisen in experiment 2 of study 1. In this experiment, after the exposure phase, participants had to observe grammatical and non-grammatical sequences passively, which we can argue could have led to the acquisition of the error. However, this did not lower the results in the final grammatical test, probably due to the extended exposure period of five days.

In study 2, we opted for a significant change in the method used to assess implicit learning by employing a statistical learning task instead of the artificial grammar learning paradigm used in the other studies. This choice was essentially due to practical issues, namely, the fact that we wanted to replicate Arciuli and Simpson's (2012) study with a different orthography and with a larger sample (making the option of presenting the artificial grammar learning task for several days impractical). In addition, previous studies showed that the statistical learning task provided evidence for long-lasting implicit learning (e.g. Arciuli & Simpson, 2012a; Kim et al., 2009). As already argued in the study 2 discussion section, the performance on the test phase was disrupted in the course of the task, and participants' performance begin to decline throughout the task. Approximately half-way through the task, participants that were able to distinguish between previously presented triplets and new triplets unexpectedly showed a performance at chance level or reversed performance (choosing the new triplets as previously presented). This occurred because participants were not instructed that the same amount of new and old triplets appeared in the test phase, and since each new triplet appeared 16 times each, participants started to second-guess their choices and accept the new triplets as old ones. Due to this unforeseen setback, we decided to perform all the posterior analysis considering only the first half of the test, but future studies should consider making alterations to this test or, at least, drawing the attention of participants of the repetitive nature of the stimuli, minimizing the acquisition of new triplets knowledge during the test phase.

Despite of the method employed in each study and the described limitations that occurred, we believe that there is evidence of implicit learning in all studies. In addition to the essential criteria of performance above chance levels (or above preference baseline performance), both in the artificial grammar learning tasks presented in studies 1 and 3 and in the statistical learning task adopted in study 2, there were no reports of explicit knowledge by the participants. There was, however, partial knowledge of fragments of the grammatical strings (in the AGL tasks) or of two out of three triplets (in the statistical learning task). Furthermore, even when it did not reach significance (as in study 1), we observe an influence of this fragment knowledge in participants' performance. Despite this influence, performance on the implicit learning tasks cannot be explained only by this fragment knowledge, and thus implicit processes still occurred. Although the focus of these studies was to isolate the implicit learning processes in order to study them (in line with what it is done in the implicit learning literature), implicit and explicit learning might not operate separately in real-world situations. It is probable that in real contexts, there is mixture of implicit (or incidental) and explicit (or intentional) learning, implying that implicit processes typically do not operate on their own (Pacton & Perruchet, 2008). This combination was probably reflected in our studies, where we observe an influence of explicit knowledge (the fragment knowledge) and implicit processes (demonstrated by the performance above chance level/baseline despite unawareness of the underlying rules/triplet sequences). Further studies are needed to assess how explicit knowledge can be combined with implicit learning and how these processes interact.

In this thesis, we explored the use of written language regularities that are not taught when formal literacy is acquired. Although those orthographic regularities have not been explicitly addressed in formal teaching, we observed a trend for the use of specific frequent orthographic patterns. The most common and logical assumption is that if these patterns are used and not explicitly taught, then they must have been implicitly acquired. An important approach in study 2 was the establishment of a link between literacy skills and implicit learning through a correlational study with typical adult readers. Although we cannot infer causality from a correlational study, our results present evidence that the participants' variance in the literacy measures goes hand-in-hand with their implicit learning skills variability. This evidence led to the questioning of whether dyslexics' deficits could be, at least in part, due to implicit learning deficits. We saw that this was not the case, as dyslexic children present a similar implicit learning performance as typical readers do. Our studies open the way to new studies that can test the impact of the implicit learning skills on the extraction of the implicit regularities present in the conversion between written and oral language. For example, it would be interesting to study whether individuals extract reading regularities, such as untaught stress syllable patterns. It would be also interesting to assess whether dyslexics extract the implicit regularities present in written language, as typical readers do. If this extraction depends only on implicit learning processes, then the performance would be similar to that of typical readers, and this opens up new fields in remediation programmes.

There are several possibilities to extend the research presented in this thesis into research from a more practical perspective. One straightforward suggestion that can be offered is that it is important that children read a lot. By doing so, they will learn about the orthographic patterns in written words and about links between spellings and linguistic units through exposure to words as they read. The implicit extraction of the untaught written regularities will also take place (boosted, as we saw, by implicit learning abilities), thus reinforcing the reading and writing proficiency. Although this suggestion is very attractive, it is usually not viable for either motivational reasons (in children that do not find reading a pleasant activity), or for clinical difficulties that prevent proficient reading (such as in dyslexia). It is important, however, to find alternatives that are more appealing, such as computer games that include specific regularities embodied in stimuli, potentiating the acquisition of these implicit regularities in both typical readers and individuals with reading and writing disorders (Apfelbaum, Hazeltine, & McMurray, 2013; Protopapas et al., 2017). It would therefore be useful to create materials that take advantage of these implicit learning processes for clinical and educational purposes.

In conclusion, the work presented in this thesis has a twofold contribution to the discussion of the mechanisms of implicit learning. First, we showed how implicit learning can be measured without explicit interference, presenting, for the first time, evidence of an eye-tracking signature of implicit knowledge in artificial grammar learning tasks. This method can be particularly useful, for example, in studying implicit learning in children. Secondly, we investigated the influence of implicit learning in literacy proficiency and how implicit learning operates in reading disabilities. This thesis provides evidence that implicit knowledge variability goes hand-in-hand with literacy proficiency, and that an implicit learning deficit does not seem to be an underlying cause of dyslexia.

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## APPENDIX 1

### Example of Stimulus Material Used in Experiment

| HG items | ACS |
|---|---|
| M-S-S-S-V-R-X-V-R-X-V-S | 61.47 |
| M-S-V-R-X-V-R-X-R-R-R-R | 53.38 |
| M-V-R-X-S-S-S-V-R-X-R | 63.63 |
| M-S-V-R-X-S-S-S-S-S-S-V | 58.52 |
| V-X-V-R-X-S-S-S-S-S-S-V | 55.48 |

| HNG items | ACS |
|---|---|
| M-**X***-S-S-V-R-X-V-R-X-(**S**)-<u>S</u> | 61.79 |
| M-S-V-R-X-V-R-X-(**S**)-**X***-R-R | 53.33 |
| M-V-R-X-(**R**)-**X***-<u>S</u>-V-R-X-R | 61.32 |
| M-S-V-R-X-S-S-(**V-R**)-S*-S-V | 58.76 |
| V-X-V-R-X-S-S-(**V-R**)-<u>S</u>*-S-V | 55.71 |

| LG items | ACS |
|---|---|
| V-X-S-V-R-X-R-R-R-M | 46.76 |
| M-S-S-S-V-R-X-R-R-R-M | 48.05 |
| M-S-S-S-S-S-S-S-V-S | 44.76 |
| V-X-S-S-S-S-S-S-S-V-S | 44.95 |
| M-S-S-S-S-S-S-S-S-V-S | 44.95 |

| LNG items | ACS |
|---|---|
| V-X-S-V-R-X-(**V**)-**X***-R-M | 46.82 |
| M-S-S-S-V-R-X-(**V**)-**X***-R-M | 48.11 |
| M-S-S-(**V-R**)-<u>S</u>*-S-S-V-S | 45.06 |
| V-X-S-S-(**V-R**)-<u>S</u>*-S-S-V-S | 45.21 |
| M-S-S-(**V-R**)-<u>S</u>*-S-S-S-V-S | 45.21 |

*Note.* Associative chunk strength (ACS) frequency distribution of two and three letter chunks in relation to the acquisition stimuli: Each letter sequence is decomposed into two and three letter chunks, and the frequency of these chunks in the acquisition sequences is calculated. Example of the calculation of ACS: MSSVRXVRXVS is decomposed in the bigrams MS (40), SS (59), SV (87), VR (97), RX (97), XV (50), VR (97), RX (97), XV (50), VS (16). The frequencies of these bigrams in the learning sequences are shown in parenthesis. The sequence was also decomposed in the trigrams, MSS (27), SSV (59), SVR (75), VRX (97), RXV (37), XVR (41), VRX (97), RXV (37), XVS (8). The ACS of this item was calculated by averaging its different bigram and trigram frequencies. The obtained ACS is 61.47. It indicates that the item's fragments were highly frequent in the acquisition set (high ACS item). The non-grammatical (NG) items were derived from the grammatical (G) sequences by, first, switching letters in two nonterminal positions (in bold). In most cases, switched letters violated the grammar (*X* in M-**X***-S-S-V-R-X-V-R-X-(S)-S), in other cases they did not (the second *S* in M-S-V-R-X-VR-X-(S)-**X***-R-R, in parenthesis). So, we then looked for the first violating letters (*X*, marked with an asterisk) and selected it as the critical trigger event. HG = high grammatical; HNG = high non-grammatical; LG = low grammatical; LNG = low non-grammatical.

# APPENDIX 2

## “Monster” stimuli used in the statistical learning task

Stimulus A

Stimulus B

Stimulus C

Stimulus D

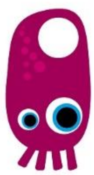
Stimulus E

Stimulus F

Stimulus G

Stimulus H

Stimulus I



Stimulus J

Stimulus K

Stimulus L

# APPENDIX 3

**Stimulus material**. Mean ACS (standard deviations in parenthesis and range in brackets) and length distribution for sequences used in acquisition and classification tasks.

| | n | Mean ACS | % of stimulus type per sequence length | | | |
|---|---|---|---|---|---|---|
| | | | 4 letters | 5 letters | 6 letters | 7 letters |
| **Acquisition Set** | 36 | 15.73 (1.49) [10.40 - 18.33] | 13.9 | 22.2 | 25.0 | 38.9 |
| **Classification Set** | | | | | | |
| GH | 10 | 15.61 (1.75) [12.64 - 17.45] | 0 | 10 | 30 | 60 |
| GL | 10 | 8.37 (2.46) [4.73 - 12.09] | 0 | 20 | 30 | 50 |
| NGH | 10 | 15.45 (1.87) [12.36 - 17.64] | 0 | 10 | 30 | 60 |
| NGL | 10 | 8.11 (2.44) [4.45 - 12.00] | 0 | 20 | 30 | 50 |

ACS = Associative chunk strength, G = Grammatical, NG = Non Grammatical, H = High ACS, L = Low ACS

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