Statistical Learning: The role of implicit and explicit processes in sequential regularities

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Abstract

Within cognitive psychology, Statistical Learning (SL) refers to our use of the statistical information available in our sensory environment to extract relationships between stimuli which unfold over time. SL enables us to use previous and current events to make predictions on upcoming ones, and it is at the basis of a number of cognitive functions (Bertels, Boursain, Destrebecqz, & Gaillard, 2015a). Aiming to address the lack of systematic investigations in the area, this thesis is concerned with the type of knowledge which results from auditory and visual SL, and whether it is implicit, unconscious, or explicit, conscious. We aimed to address existing methodological challenges around the measurement of conscious knowledge through the adoption of a novel use of the Process Dissociation Procedure in the context of a forced-choice task, in combination with the guessing and zero correlation criteria. Chapter 2 established the use of measures to assess the status of conscious knowledge of auditory stimuli generated through a transition matrix. We found successful learning of these stimuli in both adults and children, and that both age groups develop an awareness of the knowledge that they had acquired. In Chapter 3 we studied knowledge status in a triplet learning paradigm in both the auditory and visual modality. Our measures indicated that participants were fully aware of the visual and auditory stimuli learned. Chapter 4 was aimed at validating and consolidating our findings of explicit knowledge by using a combination of direct and indirect measures in a visual triplet learning paradigm, and additionally compared adults and children. The knowledge acquired was prevalently explicit in both age groups. We also found that participants' awareness of the acquired knowledge did not coincide with the ability to reproduce the training material in a generation task. Chapter 5 investigated the hypothesis that implicit and explicit knowledge are dependent on the speed of stimulus presentation. We found that, although statistical learning can take place at different presentation speeds, participants' knowledge is weaker at a faster speed.

Knowledge appeared more implicit at faster stimulus presentation speeds and more explicit at slower speeds. In Chapter 6 we investigated the electrophysiological correlates of implicit and explicit knowledge in visual statistical learning. There were no differences in in ERPs between implicitly and explicitly-learned stimuli in either learners or non-learners within our sample. However, we found suggestions that a learning effect may be present and detectable through the ERPs in the absence of above-chance behavioural performance. This PhD builds on, and extends, the existing literature, and sheds light on the theoretical and methodological challenges inherent to the behavioural approach in statistical learning. We put forward the hypothesis that knowledge measured behaviourally tends to become more explicit, the greater the learning effect, and that contradictions between measures of conscious knowledge arise in the presence of low learning. We explore promising approaches for future research to advance knowledge about statistical learning and the type of knowledge acquired, and we make a case for the use of combined electrophysiological and behavioural methods.

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Chapter 1 Introduction and literature review

1.1 The statistical learning ability in nature

Learning can be defined as the process through which, having encoded a specific input, or stimulus material, we update our internal representations regarding that input by acquiring the relationships between elements within it and, by doing so, we improve our processing of it (Frost, Armstrong, Siegelman, & Christiansen, 2015). This ability to extract meaningful information from a noisy input to acquire complex relationships between stimuli is essential during development. For this reason, the understanding of the specialised mechanisms which underlie the extraction of regularities is a very important field within cognitive psychology (Rabagliati, Ferguson, & Lew-Williams, 2018).

This thesis is specifically concerned with Statistical Learning (SL), a term which has a dual meaning. Within the machine learning approach, SL is concerned with the building of learning algorithms which can generalise from statistically structured data (Vapnik, 1999) and, within cognitive psychology, it is concerned with human learning of statistically-structured stimuli. In this thesis, we are only concerned with this latter, cognitive psychological approach (Saffran, Aslin, & Newport, 1996). The term Statistical Learning, within cognitive psychology, was first used by Saffran et al. (1996) in an artificial language acquisition experiment in which 8-month-old infants were made to passively listen to a continuous stream of artificial speech made of a random concatenation of fixed three-syllable words, or units. The authors used the term "statistical learning" to refer to the finding that their participants were able to segment the continuous artificial speech into "words" solely on the basis of transition probabilities between syllables, which were high between syllables inside a word and low across word boundaries, and to distinguish these word-like units from other, previously unseen, word-like units. In this sense, SL entails making use of the statistical information available in our sensory environment to extract relationships between stimuli which unfold over time. This ability is crucial in a complex environment because it enables us to use previous and current events to make predictions on upcoming ones, and it is at the basis of a number of cognitive functions (Bertels et al., 2015a).

Within the context of language research, SL has provided a way to study, under controlled laboratory conditions, several important mechanisms which underpin language acquisition. In fact, SL has been found to enable us to make use of various types of statistics within the language input. One of the ways in which statistical information is used during development is for the purpose of word segmentation (Saffran & Kirkham, 2016), which is the context in which SL research was born. However, several other ways in which we make use of statistical information through SL mechanisms have been discovered. Word-meaning mapping, the formation of morphosyntactic categories and spelling are only a few examples (Plante & Gómez, 2018). Indeed, SL mechanisms have been found to be involved in reading aloud because they allow learners to detect the orthographic cues which point to lexical stress, a crucial mechanisms in reading (Arciuli, 2018). SL also plays a role in the ability to spell, as the regularity extraction mechanisms allow learning of the graphotactic patterns of written language, that is, rules as to how words are spelled (Treiman, 2018). Furthermore, performance in an SL task has been found to be related to syntax acquisition mechanisms in children (Kidd, 2012). This evidence is further supported by correlational data indicating that SL is predictive of reading ability in children (Torkildsen, Arciuli, & Wie, 2019). Research has also made great progress in terms of the practical application for SL. For example, more recent work is developing ways in which SL can be used as the basis to develop language therapy interventions for children with a language development disorder (Plante & Gómez, 2018) and how it can be used for the improvement of spoken language in children with Cochlear implants (Deocampo, Smith, Kronenberger, Pisoni, & Conway, 2018).

As a mechanism capable of acquiring knowledge of relationships within a complex environment, SL is also studied within music cognition. It in fact plays a role in the acquisition and perception of musical structures (Rohrmeier & Rebuschat, 2012). SL paradigms using music stimuli created in the laboratory have been used to understand the limits to the SL mechanisms, such as the possibility to acquire local and non-local dependencies in music (Dienes & Longuet Higging, 2004; Kuhn & Dienes, 2005).

In this section we have seen that SL is a promising mechanisms to study for the understanding of a variety of important cognitive functions in humans. This thesis is specifically concerned with the type of knowledge which results from SL, and whether it is implicit, unconscious, or explicit, conscious, a topic which will be dealt with more in depth in the upcoming sections of this chapter.

In order to capture the variety of paradigms that experimental cognitive psychology has developed to study our ability to extract regularities from a noisy input, we have developed the term Sequential Regularities Learning (SRL), intended by us, generically, as the ability to uncover the underlying structure of regular patterns which unfold over time in the visual, auditory and tactile environments. This new term is also intended to avoid the existing confusion around terminology in the field, in which the term “Statistical Learning” is taken by many authors to mean “Implicit Learning” (Perruchet, 2006). Within Sequential Regularities Learning, tasks have been developed which require the learning of transitional probabilities between elements in sequential stimuli, which are the focus of this thesis. This specific type of extraction of regularities, that is, the extraction of transition probabilities, is strictly referred to as Statistical Learning (SL). However, other paradigms have been developed, such as Artificial Grammar Learning which are based on a different type of statistical structure, but greatly overlap with statistical learning in the strict sense, and have been used to investigate very similar research questions. In this thesis, we will make use of the term Statistical Learning to refer to paradigms which use transition probability statistics and the term Sequential Regularities Learning to refer to Statistical Learning paradigms and Artificial Grammar Learning.

1.2 Sequential regularities learning in the laboratory

1.2.1 The paradigms and the basis for their classification

Sequential regularities learning has been measured in a laboratory context through the use of Artificial Grammar Learning (AGL), Statistical Learning (SL) and the Serial Reaction Time Task (SRTT), which is classed as motor SL. These have traditionally been referred to as implicit learning tasks (Curran, 1997; Jenny R. Saffran, Newport, Aslin, Tunick, & Barrueco, 1997; Daniel B Willingham, Wells, Laura, Farrel, Jeanne, & Stemwedel, Maurine, 2000). The types of regularities which underpin sequential regularities learning paradigms can be broadly classified into two categories, investigated by three different types of experimental tasks: rule-based regularities (Artificial Grammar Learning) and regularities based on transition probabilities in motor (Serial Reaction Time Task) and non- motor (Statistical Learning) tasks. Although AGL is not statistical learning in the strict sense, as it is a task primarily designed for the study of rule acquisition, it plays an important role within this thesis. Firstly, it is analogous to statistical learning in more than one respect: the structure of the testing sessions, comprised of a learning phase and a test phase, and the fact that learning still relies on sensitivity to statistical properties of the input stimuli. Secondly, many of the research questions in SL are also relevant to AGL, and vice-versa. This includes questions on the implicitness of the learning (Kim, Seitz, Feenstra, & Shams, 2009), which, being the key research question of this thesis, will be dealt with in more detail in the upcoming sections.

1.2.2 Artificial Grammar Learning (AGL)

In the seminal paper by Reber (1967), the term “implicit learning” was first introduced in the literature to account for findings of an Artificial Grammar Learning (AGL) experiment. In the exposure phase participants were required to memorise letter strings generated from a finite-state grammar. In the test phase they were asked to classify new strings as grammatical, if they were consistent with the finite- state grammar, or ungrammatical, if they did not follow the grammar. Classification responses were found to be correct in 79% of cases. However, participants were not able to answer questions about the rules governing the sequence, which suggested that they lacked explicit knowledge.

Findings of above- chance classification performance are typical (Reber, 1976; Dienes, Broadbent, & Berry, 1991; Kinder & Assmann, 2000; Lotz, A., Kinder, 2006; Mathews et al., 1989; Pothos & Bailey, 2000), but it is still an open topic of debate exactly what form is taken by the knowledge acquired and, consequently, how classification performance can be explained. Implicit learning was seen by Reber (1989) as producing abstract knowledge about the structure of stimuli which can be used to make decisions about novel stimuli in the absence of knowledge that can be verbalised about the grammar rules. Some of the later research attempting to verify the implicitness of knowledge acquired in AGL has, indeed, found support for this view (Allwood, Granhag, & Johansson, 2000; Channon et al., 2002; Dienes & Altmann, 1997; Dienes & Perner, 2003; Tunney & Altmann, 2001).

Proponents of an alternative account hold that grammaticality judgments are based on the similarity between novel stimuli presented in the test phase and either whole stimuli, or fragments of these, memorised in the exposure phase. The knowledge acquired therefore takes the form of explicit chunks of training stimuli, rather than abstract representations which are independent of the surface properties of the specific stimuli (Pierre Perruchet & Pacteau, 1990; Brooks, Lee & Vokey, 1991; Kinder & Assmann, 2000; Pierre Perruchet & Rey, 2005; Vokey & Brooks, 1994; Dulany, Carlson, & Dewey, 1984; Servan-Schreiber & Anderson, 1990; Boucher & Dienes, 2003; Johansson, 2009). Although this dispute is far from settled, there is evidence to suggest that the acquisition of both grammar rules and parts of the training stimuli play a role in grammaticality classification performance (Domangue, Mathews, Sun, Roussel, & Guidry, 2004; Knowlton & Squire, 1996; Meulemans & Van der Linden, 1997; Opitz & Friederici, 2004; Hauser, M. Hofmann, J., Opitz, 2012; Opitz & Hofmann, 2015). For a discussion of theories on the factors which underlie performance in AGL see Pothos (2007).

1.2.3 Statistical learning

1.2.3.1 Motor learning: the Serial Reaction Time Task (SRTT)

In the SRTT task (Nissen & Bullemer, 1987) participants are instructed to respond as quickly and accurately as possible to a visual target appearing at different locations on the screen, typically three to six. Each location requires a specific finger response (key press). The target transitions can either follow a fixed sequence, in the deterministic version of the task, or follow a sequence with a certain probability, in the probabilistic version (Schvaneveldt & Gomez, 1998). In the course of training, participants learn the structure of the repeating sequence, as evidenced by longer Reaction Times (RTs) to respond to trials in the unlearned sequence (transfer sequence) than the repeating sequence (Martini, Furtner, & Sachse, 2013; Cleeremans, Destrebecqz, & Boyer, 1998), by the RT difference between predictable and unpredictable trials (Cleeremans & McClelland, 1991) or by shorter RTs in later than earlier blocks (Abrahamse, van der Lubbe, Verwey, Szumska, & Jaśkowski, 2012; Willingham, Nissen, & Bullemer, 1989).

Due to the kind of motor skill learning acquired, the SRT task is often portrayed as an example of implicit learning (Abrahamse, Jiménez, Verwey, & Clegg, 2010). In fact, serial regularities are learned as a sequence of motor responses made when pressing the correct sequence of response buttons (Robertson, 2007). The implicit processes for the prediction of future events which are involved in motor learning tasks such as this are underpinned by a distributed brain network which works dynamically (Altamura, Carver, Elvevåg, Weinberger, & Coppola, 2014). Research indicates that procedural implicit learning in SRTT can proceed in the absence of awareness of the sequence (Willingham et al, 1989; Willingham, Salidis, & Gabrieli, 2002; Cleeremans & McClelland, 1991; Tim Curran & Keele, 1993; Lewicki, Pawel; Hill, Thomas; Bizot, 1988; McDowall, Lustig, & Parkin, 1995; Reed & Johnson, 1994; Stadler, 1989; Rose, Haider, Salari, & Buchel, 2011), although it is also possible to acquire explicit knowledge of some or all of the sequence (Perruchet & Amorim, 1992; Brown & Robertson, 2007; Dale, Duran, & Morehead, 2012).

1.2.3.2 Sequences with transition probabilities based on word-like units

The term statistical learning was first introduced by (Saffran, Aslin, & Newport, 1996) in the context of language acquisition, specifically, speech segmentation. The authors exposed 8-month-olds to an auditorily-presented continuous stream of artificial speech which was composed of trisyllabic elements (“words”). The only cue to segmentation of words in the stream was the higher probability for transitions of syllables within words than between words. Infants were found to be able to segment the words embedded in the stream on the basis of transitional probabilities between syllables after two minutes of exposure, as shown by their ability to discriminate between words and non- words in the test phase (Saffran et al., 1997). Learning to extract regularities from the stimulus stream on the basis of transitional probabilities is a finding that has been replicated not only in the domain of artificial speech (Graf, Evans, Alibali, Saffran, & Estes, 2007; Franco, Gaillard, & Destrebecqz, 2014; Franco, Cleeremans, & Destrebecqz, 2011a), but also in the processing of tone stimuli (Saffran, Johnson, Aslin, & Newport, 1999; Creel, Newport, & Aslin, 2004) and of visual shapes (Kirkham, Slemmer, & Johnson, 2002; Fiser & Aslin, 2002a; Turk-Browne, Jungé, & Scholl, 2005; Schapiro, Gregory, Landau, McCloskey, & Turk-Browne, 2014). Given that the statistical structure of the stimulus in this paradigm is given by a concatenation of three-element chunks, this paradigm is also commonly referred to as the Triplet Learning (TL) paradigm. A disadvantage of the classic task by Saffran, Aslin and Newport (1996) is that it does not have control over first and second-order probabilities, which are mixed within the stimulus stream. However, the fact that the stimulus stream is constructed on the basis of “words” or chunks, also referred to as “triplets”, makes this task practical when it comes to testing participants’ discrimination between trained and untrained triplets.

1.2.3.3 Sequences with transition probabilities based on transition matrix

Structured stimuli have also been created by using a transition matrix which determines the probability of transitioning from one element to another in a sequence. This way, any given stimulus can be associated to a certain degree to multiple other stimuli. For an example of tone sequences based on second order dependencies generated by a transition matrix see (Durrant, Taylor, Cairney, & Lewis, 2011a; Durrant, Cairney, & Lewis, 2013a). The main advantage of the transition matrix task is that it offers full control over the types of probabilities contained in the stimulus stream (first or second order) and, thanks to this flexibility in the construction of the statistically structured stimuli, it has high ecological validity. The stimulus stream, however, does not contain designed chunks, or "words", and therefore the test phase requires longer sequences for comparison.

1.2.3.4 Individual differences in statistical learning

Statistical Learning research has more recently begun to shift the focus from group performance to performance at the individual level, highlighting the fact that, typically, the majority of participants in classic Statistical Learning tasks perform around chance, whilst only a few participants achieve a high proportion of correct responses (Siegelman, Bogaerts and Frost, 2017). Within this context, understanding the source of individual variability in task performance has become a more important research goal, and a number of large correlational studies have been devoted to the investigation of the relationship between Statistical Learning and other cognitive abilities, aiming to understand what drives between-participants differences.

The majority of work has been undertaken with linguistic abilities, showing evidence that Statistical Learning is positively correlated with performance in a number of language-related tasks (Misyak and Christiansen, 2012). Conway et al. (2010) explain this relationship by postulating that the common factor underlying performance in statistical learning tasks and tasks involving natural language is participants' sensitivity to the statistical structure of stimuli. In infants and children, performance in a visual triplet learning task was found to positively correlate with their level of language development (Shafto, Conway, Field & Houston, 2012). Performance in a visual statistical learning task is also widely agreed to play an important role in reading ability for both adults and children, once age and attention are controlled for (Arciuli and Simpson, 2012). Regarding the relationship between statistical learning and other non-linguistic cognitive tasks, performance in an auditory statistical learning tasks using an artificial language was found to correlate positively with fluid intelligence, measured by the Culture Fair Intelligence Test, verbal working memory and short-term memory span, as measured by a forward digit span task (Misyak and Christiansen, 2012). It is worth noting that the methodological differences between the various statistical learning tasks and cognitive performance measures used make comparison across studies difficult, and that therefore drawing a complete picture of the source of individual variability in SL is an ongoing challenge for research. These are very worthwhile efforts, however, which will shed light on the complex question of what the Statistical Learning ability is, and what it entails.

1.2.3.5 The implicitness of statistical learning

The terms statistical learning and implicit learning have been often used interchangeably (Pierre Perruchet & Pacton, 2006). The implicitness of statistical learning is supported by the fact that participants are unaware of the statistical structure of the stimuli (Fiser & Aslin, 2002b), by the incidental nature of the acquisition (Fiser & Aslin, 2001; Fiser & Aslin, 2005) and by the presence of this kind of learning in infants (Saffran et al., 1996; Fiser & Aslin, 2002c; Aslin, Saffran, & Newport, 1998; Graf et al., 2007) and non-human primates (Hauser, Newport, & Aslin, 2001; Goujon & Fagot, 2013). Despite this, there is also evidence from triplet learning studies that it is possible to acquire explicit knowledge of the word-like units embedded in the stimulus stream (Bertels, Boursain, Destrebecqz, & Gaillard, 2015b; Franco, Cleeremans, & Destrebecqz, 2011b).

1.3 Statistical Learning within the wider context: related theories and approaches to the study of learning

This Thesis is specifically concerned with the Statistical Learning (SL) approach to the study of learning, and with the use of paradigms in which the statistical regularities of the to-be-learned stimuli are determined by the transition probabilities between elements. However, it is important to note that SL is closely related to a number of other theories and approaches to understanding learning. In this section we focus specifically on predictive coding, reinforcement learning, domain-specific statistical learning models of music, and provide a brief overview of two well-established probabilistic learning paradigms. We aim to show the ways in which these theories and approaches relate to SL, putting SL into the wider context of learning research. In line with the definition of learning by Frost et al. (2015) which we have adopted in thesis, the different theories outlined in this section are concerned with a common object of study, that is, how we encode input and acquire relationships between elements within that input, which then allows us to improve our processing of it. Due to the links between SL and other neighbouring approaches to learning, the understanding regarding the roles of implicit and explicit knowledge which we will gain in this thesis will also shed light on implicit and implicit knowledge in learning more widely.

One theory closely related to the SL approach is predictive coding, which postulates that the brain builds a model of the environment from which predictions are generated. These are then compared to actual sensory input and adjusted accordingly, therefore the model is constantly updated on the basis of the feedback obtained (Clark, 2013). Predictive coding has its roots in early cognitive theories on visual processing taking a top-down approach to visual perception, in which the brain's predictions are constantly adjusted on the basis of the feedback received by the visual input (Rajesh, Rao & Ballard, 1999). The theory incorporates a way for the cognitive system to deal with the statistical noise that is present in our world. This relies on the concept of "precision weighting", whereby the precision of our predictions about the world is represented. This can then be changed and adapted to various contexts. Having a measure of the precisions of our predictions helps us in keeping prediction error to a minimum (Feldman & Friston, 2010; Friston, 2009). The key concepts put forward by predictive coding are also used in the field of computational neuroscience and form the basis of machine learning and neural networks models, which are promising for the development of our understanding of complex tasks such as object recognition and the understanding of speech (Hinton, 2007).

Perceptual processing has been one of the key areas which predictive coding has focused on. The study of perceptual processing in infants has provided evidence for the theory, showing that perception happens in a top down fashion, with expectations about sensory input already observable in infants (Emberson et al., 2015). For the purpose of situating our work in this thesis into the context of the wider literature, it is worth noting that both SL and predictive coding are focused on understanding how we learn about, and process, different types of information in the world around us. In fact, whilst the SL approach places its emphasis on how regular patterns are extracted from sequential stimuli in the environment, predictive coding focuses on the formation of expectations regarding our sensory environment. Both approaches are ultimately concerned with how humans use the information learned from the input stimuli to generate predictions about the surrounding world.

The cognitive psychological approach to understanding learning has also focused on the building of algorithms that would model cognitive functioning. Computer systems are important for our understanding of human learning as they allow to "reverse engineer" the process of how our minds are able to make inferences based on the data available in our environment (Tenenbaum, Kemp, Griffiths & Goodman, 2011). In this respect, we believe that reinforcement learning and its connections to SL are worth mentioning. Within the field of machine learning, reinforcement learning, in a similar way to supervised and unsupervised learning, studies how an "agent", or system, works to maximise reward whilst interacting with a dynamic environment. In the reinforcement learning mechanism, actions which lead to an increase reward subsequently increase in frequency (Huys &Dayan, 2009).

Within the field of psychology, reinforcement learning is useful in understanding the cognitive and neural mechanisms which underpin our learning from, and interaction with, our environment. For example, it can be used to explain how learning about the statistical properties of an environment is then used to guide reinforcement learning in subsequent interactions with other environments (Chater, 2009).

This approach is closely linked to the SL approach adopted in this thesis, with differences between the two often coming down to terminology. In fact, both approaches can be used to understand how our minds are able to make inferences and predictions using the data available in the environment. In a similar way to the use of transition probabilities in SL, reinforcement learning uses the concept of Markov entropy to formalise the variability of the different outcomes for each action by the agent. When an action deterministically leads to an outcome, entropy is low, whilst if an action leads to multiple possible outcomes with similar probability, entropy is high (Huys &Dayan, 2009). In this thesis, we also make use of a probabilistic or deterministic transition matrix to manipulate entropy in our stimuli.

The concept of Markov entropy is also at the basis of domain-specific statistical learning models in music, such as IDyOM (Information Dynamics of Music) (Pearce, 2005). The IDyOM model aims to understand the formation of expectation through learning of the statistical regularities acquired through exposure to music (Pearce, Müllensiefen & Wiggins, 2010). Unlike our work in this Thesis, IDyOM is therefore based on real-life stimuli.

The IDyOM software is a Markov model for statistical modelling of musical structure which is able to represent the likelihood of each note within a melody given the musical context which precedes it (Pearce, Müllensiefen & Wiggins, 2010). Therefore, in the same way as our SL approach, IDyOM quantifies the probability of occurrence of each element within sequential stimuli based on the previous one(s), therefore also providing a measure of the level of entropy in the stimuli. Given the closeness of these two strands of work, we anticipate that any insight gained in this thesis into explicit and implicit knowledge in statistical learning will also set the basis for future work with real-life music stimuli.

To conclude our overview of SL in the context of closely related theories and paradigms, it is also important to draw the reader's attention to two long-established and widely-used probabilistic learning paradigms: the Iowa gambling task (Bechara, Damasio, Damasio & Anderson, 1994) and the Weather Prediction task (Gluck, Shohamy & Myers, 2002). In the Iowa gambling paradigm, initially developed for the study of patients with damage to the ventromedial prefrontal cortex, and the decision-making impairments that this caused (Bechara, Damasio, Damasio & Anderson, 1994), participants engage in a probabilistic learning task, in which they are presented with a number virtual decks of cards which can either hold rewards or penalties, and are asked to aim to maximise their rewards whilst sampling the decks. Unbeknownst to the participants, some decks contain more frequent rewards than others. Typical findings are that, after sufficient sampling of each deck, participants learn to sample the decks in a way which avoids losses as much as possible (Brevers, Bechara, Cleeremans & Noel, 2013). The weather prediction task, developed for the specific purpose of studying probabilistic learning, involves participants uncovering a series of tarot cards which are associated with a certain probability to a weather outcome. Typical results show that, over time, participants become able to "predict the weather" on the basis of the tarot cards (Gluck, Shohamy & Myers, 2002). Whilst the main focus in SL is the extraction of transition probabilities between elements, the Iowa Gambling Paradigm and the Weather Prediction task place their emphasis on category learning. Both probabilistic learning and statistical learning, however, have been seen as a form of procedural learning (Gluck, Shohamy & Myers, 2002) and they are therefore closely related.

The paradigms and approaches reviewed in this section are linked by the common aim to study and understand learning from experience, which is a crucial ability for human functioning and survival, and a key element of what is referred to as "intelligence" (Ferreira & Dias, 2014, p. 147). They therefore share a focus on how we make sense of the statistical regularities in our environment and how we come to generalise from these data to form expectations, and consequently make predictions, about future events. Hasson (2017) defines SL as a "dynamic field" that is "changing in theoretical scope and emphasis". Following on from this, we believe it is important for researchers to consider SL not in isolation, but within the context of the neighbouring research fields that we have outlined in this section. We believe that these different theories and paradigms can aid each other in the common effort to understand how learning works.

1.4 A background to implicit learning

As outlined in previous sections, Sequential Regularities Learning has traditionally been considered a form of Implicit Learning (IL) (Pierre Perruchet & Pacton, 2006). Although from our brief outline of the four main experimental paradigms it emerged that there is some evidence for both implicit and explicit learning, the assumption that Sequential Regularities Learning and Implicit Learning overlap is still prevalent in much of the literature. Given the overlap in the two research traditions, and the fact that implicit, and conversely explicit, learning are the main object of this thesis, in this section we provide a brief historical background of Implicit Learning and present the theoretical and empirical challenges inherent to this research.

Implicit Learning, when seen as the process of acquiring unconscious knowledge, is a fundamental process which underpins a number of important cognitive functions. An example of this is the strong link between the field of IL and psycholinguistics (Rebuschat, 1994), given that language acquisition involves unintentional learning of complex information and does not require an explicit knowledge of grammar (Cleeremans et al., 1998). Other examples of functions supported by implicit learning are the area of music cognition (Rohrmeier & Rebuschat, 2012), and motor skills such as driving a car or riding a bicycle (Cleeremans & Dienes, 2008).

The many definitions of implicit learning that have been put forward differ in whether they conceptualise implicit learning as something related to the process of knowledge acquisition (the encoding) (Stadler, M.A., Frensch, 1994) or both the encoding and retrieval (Shanks & St John, 1994; Lewicki, Czyzewska, & Hoffman, 1987; Reber, 1989). In 1967, Reber first used the term "implicit learning" in the context of an AGL experiment, which was the first of many on this topic. Implicit learning was defined as a process in which complex information is acquired without the participants being aware that learning is taking place, or of the contents of the knowledge that they hold (Reber, 1967). This definition emphasises participants' lack of awareness of both the knowledge acquisition process and the products of the learning, in a way that makes the concept of implicit learning, for Reber, similar to the concept of memory retrieval (Schacter & Graf, 1985), with the exception that, with implicit learning, the emphasis is on the effects of acquiring knowledge about structural properties of the stimuli, rather than simply having had an experience with individual stimuli (Levy, 1993). Along these lines, this thesis is specifically concerned with implicit learning as applied to the products of learning, that is, we intend to focus on the awareness, or lack thereof, of the learned material. In Sequential Regularities Learning, the product of learning is the statistical structure underlying the training stimuli. Most of the literature on implicit learning has focused on the acquisition process (Forkstam & Petersson, 2005), and fewer attempts have been made to resolve current issues and debates around the awareness of the acquired knowledge in Sequential Regularities Learning.

There are several challenges of theoretical and methodological nature involved in the study of implicit learning which are, to date, unresolved and an object of debate amongst researchers in the field. The first challenge concerns the different implications, for empirical research, of definitions of implicit learning which focus on the process of acquisition and those which focus on knowledge retrieval. Critics of definitions of IL which focus on awareness of the acquired knowledge (Stadler & Frensch, 1994) point to the fact that focusing on the outcome of learning requires us to make an assumption about the process of learning, which is not being measured directly. In other words, learning in participants is assessed retrospectively, through some kind of test, after the learning has taken place, and not as it occurs, therefore a measure of the awareness of the acquired knowledge is limited to the assessment of awareness of that knowledge, which might not necessarily mirror the awareness of the learning process. When we focus on the outcome of learning we must assume, however, that unconscious knowledge measured at retrieval stems from an unconscious learning process. In order to minimise this issue, Reber (1976) recommended that researchers use the experimental setup, such as acquisition of knowledge through incidental conditions, to guarantee the implicitness of the process of learning. The issue of the separation between the knowledge acquisition process and the product of learning is a large methodological challenge in this field, and something that research is still currently working to resolve through the use of both behavioural (Bowles, 2010; Leow, 2000), and electrophysiological techniques (Mandikal Vasuki, Sharma, Ibrahim, & Arciuli, 2017).

The second challenge relates to the operationalisation of consciousness, which is the necessary next step once a definition of implicit as unconscious is adopted. The development of agreed-upon measures of conscious knowledge has been a large challenge in this field of research, which, to date, has not been surpassed. The fact that different measures of conscious knowledge lead to different results has hindered progress in the field, as there has been no consistent accumulation of evidence in favour of one operationalisation or another.

Aiming to explore the roles of implicit and explicit knowledge in Sequential Regularities Learning, this thesis will focus on the awareness, or lack thereof, of the knowledge acquired incidentally as a result of being exposed to statistically structured stimuli. For this purpose, it will be necessary to explore the available operationalisations of awareness in Sequential Regularities Learning research and assess their suitability in identifying implicit knowledge and distinguishing it from explicit knowledge. Within our framework, a demonstration of unconscious knowledge would entail the following: 1) a demonstration that learning has taken place, 2) a demonstration that the learning process was implicit, which we will assume on the basis of implicit instructions and incidental acquisition of the statistical structure in our stimuli, 3) a demonstration that the acquired knowledge is implicit, which we will be able to conclude when the criteria for "implicit" established by our chosen measure(s) of awareness are met.

1.5 Measures of implicit and explicit knowledge in sequential regularities learning research

As discussed in the previous section, our approach to implicit learning in this thesis, which defines it in terms of awareness, presupposes that implicit learning occurs when participants are not aware that they have encoded, or retrieved, knowledge. This thesis will treat the term "unconscious" as synonym with "unaware" which, according to Greenwald (1992), is its most common use and these terms will be used interchangeably with the term "implicit". In the same way, the term "explicit" and "conscious" or "aware" will be considered synonyms, and used interchangeably. The present section is specifically concerned with the measures that research has developed to assess, or quantify, implicit and explicit knowledge in Sequential Regularities Learning. These approaches to measuring implicit and explicit knowledge presuppose different distinctions between the concepts of "aware" and "unaware". Theories on the measures of conscious knowledge are therefore inextricably connected to theories about what constitutes conscious knowledge, to the point that different theories lead to the development of different methods for measuring conscious knowledge (Seth, Dienes, Cleeremans, Overgaard, & Pessoa, 2008; Destrebecqz & Peigneux, 2005b). [1]

The two main perspectives from which consciousness has been defined are the functionalist perspective, which defines consciousness in terms of the functions that it allows, such as attention, control, and memory representations (Destrebecqz & Peigneux, 2005b), and the phenomenological perspective, in which consciousness is defined in terms of the subjective experience that it entails (Destrebecqz & Peigneux, 2005b). The following sections will be organised on the basis of these two approaches.

This section provides an overview of how implicit and explicit knowledge are measured in Statistical Learning research. Although our focus in this thesis is on the product of learning, and therefore in this section we deal with measures of awareness of the acquired knowledge,

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[1] The complexity of this topic within, but not limited to, Sequential Regularities Learning research is reflected in the number of reviews published on the subject, some of which are (A. Destrebecqz & Peigneux, 2005a) (Rebuschat, 2013) and (Gaillard et al., 2014).

we will also include a brief account of the role of attention in Statistical Learning and the dual-task literature. As a large portion of research in this field has distinguished explicit and implicit learning based on their requirements for central resources, this approach deserves some consideration.

1.5.1 The functionalist approach

The functionalist perspective focuses on describing consciousness in terms of what it allows. Specifically, verbal access, measured through verbal reports, recollection, measured through forced-choice and generation tests, and control, measured through the Process Dissociation Procedure (PDP). These have also been classed as objective measures of consciousness (Destrebecqz & Peigneux, 2005b).

1.5.1.1 Verbal access

If, as Greenwald (1992) proposed, the concept of "unaware" is intended as failure to correctly report one's own experience, it follows that, if participants are unable to report information regarding the properties of the stimuli that they have learned, then they are to be considered unaware. This is the rationale underpinning the idea that participants' ability for verbal access can be used to distinguish conscious from unconscious processes.

1.5.1.1.1 Verbal reports

Verbal reports consist of asking participants to indicate what they have learned, for example, whether they are able to verbalise any grammar rules noticed during the exposure phase (Reber, 1967; Dienes et al., 1991). An inability to report this information, despite the presence of an observable learning effect, is considered evidence of unconscious learning, a conclusion that has been arrived at in several studies, for example, Williams (2005), Rebuschat & Williams, (2012), Reber (1967), Dienes et al., (1991).

Shanks & St John (1994) put forward two criteria for valid tests of awareness: the information criterion and the sensitivity criterion. According to the information criterion, to be able to conclude that participants are unaware of the information they have learned, it is necessary to establish that the information asked for by tests of awareness is the same information that has led them to the learning. The sensitivity criterion requires that tests of awareness have a level of sensitivity which is comparable to that of the tests used to demonstrate that learning has taken place. According to Shanks & St John (1994), any distinction drawn between conscious and unconscious knowledge is only legitimate if the measure of awareness used meets these two criteria. However, in the case of verbal reports, there is a possibility that participants might fail to report knowledge that is held with low confidence (Gaillard, Cleeremans, & Destrebecqz, 2014). This individual response bias can cause verbal reports to overestimate unconscious knowledge, due to their insufficient sensitivity to assess all of the participants' conscious knowledge, a methodological shortcoming which is widely agreed upon by the literature (Rebuschat, 2013). Furthermore, it is also possible that this test of conscious knowledge might require participants to use a different type of knowledge that they did not actually need for successful performance in the task. In the example of AGL, a verbal test of awareness might ask participants to verbally report the rules of the grammar. However, there is evidence that, in order to perform above chance in the forced-choice task, participants do not need knowledge of the grammar rules, and recognising specific chunks of the training strings is sufficient for successful performance (Perruchet & Pacteau, 1990; Perruchet & Rey, 2005; Boucher & Dienes, 2003; Johansson, 2009). The type of knowledge required by the forced-choice task and by the test of awareness are therefore different, which constitutes a violation of the information criterion.

Another methodological concern around the use of verbal reports as a measure of awareness is something that also affects other measures of conscious knowledge (Eimer, Goschke, Schlaghecken, & Stürmer, 1996), and this the problem of participants forgetting what they have learned between the training and the test phase. The issue stems from the fact that all reports of awareness made during the test phase are retrospective in nature, which implies that, if participants display little or no awareness during the test phase, it cannot be assumed that this is because they lacked awareness during training. Although attempts have been made to measure awareness during encoding (Bowles, 2010; Leow, 2000), these techniques rely on participants "thinking aloud" as they are receiving training, and they have only been applied to the field of second language acquisition so far. We hold that more work would be needed on this technique for its successful application to Sequential Regularities Learning paradigms without raising methodological concerns about the technique interfering with the learning process.

The low validity and reliability of verbal reports is a concern that has been widely acknowledged in very early, more general research (Adams, 1957; Eriksen, 1960; Holender, 1986) and later literature, more specific to Sequential Regularities Learning (Shanks & St John, 1994; Hannula, Simons, & Cohen, 2005). The consensus is that the empirical usefulness of verbal reports is limited and that they should not be used in experimental investigations as the sole measure of conscious knowledge.

1.5.1.2 Recollection

Within the functionalist approach, consciousness is seen as enabling recollection, which means that participants are considered to have developed conscious knowledge of the statistical structure of the training if they are able to successfully perform in a test phase, administered after exposure. Tests are usually in the form of forced-choice tests or generation tests (Gaillard et al., 2014).

1.5.1.2.1 Forced-choice tests

In Sequential Regularities Learning, forced-choice tests have taken the form of either old/ new recognition judgements on fragments of the training material (Turk-Browne, Scholl, Johnson, & Chun, 2010) or multiple-choice tests, such as two-alternative forced-choice (2AFC) tasks or four-alternative forced-choice (4AFC) tasks (Bertels et al., 2015b; Bertels, Franco, & Destrebecqz, 2012a). For example, based on the assumption that consciousness enables recollection, taking the example of the SRT task, if a motor advantage is observed in response times to the training sequences, and if this is complemented by participants' successful performance in a subsequent recognition task, this could be taken as evidence for explicit knowledge (Perruchet & Amorim, 1992).

Reingold & Merikle (1988) proposed the exclusiveness assumption as necessary for a suitable test of awareness. This requires that a test of explicit knowledge is sensitive exclusively to conscious knowledge. However, forced-choice measures of explicit, or conscious, knowledge, fail to meet this assumption. In fact, it cannot be assumed that above-chance performance in forced-choice tasks is solely driven by explicit knowledge (Jimenez, Mendez, & Cleeremans, 1996a). There are other factors which drive successful performance in a forced-choice task, one of them being perceptual and motor fluency. This is an ease of processing of old test stimuli, which have been previously seen in the training, which induces a feeling of familiarity for these stimuli and might lead participants to choose them in the test (Perruchet & Amorim, 1992; Pothos, 2007). This feeling of familiarity is classed as a non-conscious process, and could potentially contaminate the forced-choice measure of explicit knowledge with implicit processing (Jacoby, 1991). The exclusiveness assumption is further threatened by the fact that judgements in each forced-choice test trial could be either based on a feeling of "remembering" or a feeling of "knowing", two attributions which are thought to correspond to explicit and implicit processing respectively by participants (Rajaram, 1993). Although there have been advancements in the development of measures of conscious knowledge, controlling these unconscious influences on performance in tasks intended to assess explicit processing is a methodological challenge that has not yet been resolved.

Overall, there are important methodological caveats to consider when assessing conscious knowledge through forced-choice tasks. These caveats are related to what is referred to in the literature as the process purity problem, that is, the fact that tasks are not solely influenced by one type of process, implicit or explicit, but, rather, both processes play a role (Reingold & Merikle, 1988). Although forced-choice tasks might detect more conscious knowledge than verbal reports, on the other hand, there is also the risk that they may be subject to unconscious influences (Gaillard et al., 2014). Using the assumption that tasks are sensitive to both implicit and explicit processes, more sophisticated measures of awareness have been developed, such as the comparison between direct and indirect tasks and the Process Dissociation Procedure (PDP), both of which will be dealt with in upcoming sections.

1.5.1.2.2 Generation tasks

Generation tasks ask participants, after training, to attempt to reproduce the learning material. They have mainly been used in the context of motor learning in the SRTT (Bischoff-Grethe, Goedert, Willingham, & Grafton, 2004; Norman & Price, 2010). According to Shanks & St John (1994), generation tasks are thought to be able to detect more conscious knowledge, compared to verbal reports and forced-choice tasks, and are therefore better qualified to fulfil the information and sensitivity criteria. The authors attribute this to the fact that generation tasks use similar retrieval conditions to the learning task. We suggest that there may be occasions in which there is a lack of complete similarity between the learning task and the retrieval task. For example, in the case of an SRTT, the learning task requires participants to follow visual cues on the screen which guide them as to which key to press for response. In contrast, during an SRTT generation task, on-screen cues only appear once a button has been pressed by the participant (Bischoff-Grethe et al., 2004; Norman & Price, 2010). Nevertheless, we suggest that, given their complete reliance on recollection of the learned material, generation tasks are highly suitable for the detection of conscious knowledge.

Despite this increased sensitivity, caution is needed when interpreting results, as, in an SRT task, participants have been shown to be able to reproduce the training sequence even when claiming that they were guessing (Shanks & Johnstone, 1998). Caution is needed when interpreting these results and when applying them to other Sequential Regularities Learning paradigms. In fact, it may be possible that performance in an SRT generation task may be supported by learned motor programs, as participants are asked to use the same response keys for the generation task that they used during training. It is therefore possible that a motor program could support successful performance in a generation task in the absence of explicit knowledge of the sequence. Non-motor Sequential Regularities Learning paradigms should make more use of generation tasks to take advantage of their increased sensitivity and the access to explicit recollection that they provide, and use them in combination with other measures of awareness.

1.5.1.3 Control

1.5.1.3.1 The Process Dissociation Procedure (PDP)

The Process Dissociation Procedure (PDP) is an objective measure of awareness which aims to dissociate between conscious and unconscious knowledge, thus attempting to resolve the contamination problem which affects measures of verbal reports and recollection (Jacoby, 1991). Seeing awareness as enabling control of knowledge, it rests on the assumption that, while conscious knowledge can be controlled to fulfil task instructions, unconscious knowledge influences performance independently of volitional control (Jacoby, 1991; Jacoby, Toth, & Yonelinas, 1993). Explicit knowledge is therefore characterised as knowledge that can be subjected to volitional control (Wilkinson & Shanks, 2004a). In the context of Sequential Regularities Learning, the PDP has been mostly applied to the SRT task (Fu, Fu, & Dienes, 2008a; Fu, Dienes, & Fu, 2010a; Fu, Bin, Dienes, Fu, & Gao, 2013; Destrebecqz & Cleeremans, 2001). Only one study has applied it to auditory triplet learning, using artificial languages (Franco et al., 2011a).

After the exposure phase, participants are administered a generation or completion test twice: once under inclusion conditions and once under exclusion conditions. Inclusion instructions ask participants to either freely generate (Destrebecqz & Cleeremans, 2001) or complete based on a one or two-element cue (Fu et al., 2013), fragments belonging to the training sequence. Conversely, exclusion instructions ask participants to refrain from completing the fragments or generating fragments which belonged to the training sequence. The assumption is that, whilst inclusion performance can be influenced by both implicit and explicit knowledge, successful exclusion performance is underpinned by explicit knowledge, intended as knowledge that participants have control of (Jacoby, 1991). In the analysis of PDP data, the proportion of sequence fragments belonging to the exposure phase that are chosen or generated by participants is taken as the dependent variable, and this dependent variable is compared between inclusion and exclusion conditions, and to chance level, for example 0.5 in a two-alternative forced-choice task. Explicit knowledge is observed when the generation of training fragments is greater under inclusion than exclusion and either at chance or below chance under exclusion (Fu et al., 2010a). Implicit knowledge is observed when the generation of training fragments is not different between inclusion and exclusion and above chance under exclusion (Fu et al., 2010a).

Despite the PDP goes one step further than other measures in separating conscious and unconscious influences, it is not an unproblematic procedure (Norman, Scott, Price, & Dienes, 2016). Its assumption that conscious knowledge can be subject to volitional control can, in fact, be questioned by early findings that consciousness and control do not always go together, such as those of Broadbent (1977) that that participants can acquire the ability to control a system without any verbalisable knowledge of the rules governing it.

In terms of Sequential Regularities Learning paradigms, in fact, there are a number of studies in which participants have been shown to have control of knowledge unaccompanied by awareness of knowing (Gaillard, Destrebecqz, & Cleeremans, 2012; Destrebecqz & Cleeremans, 2003; Wan, Dienes, & Fu, 2008; Fu et al., 2010a) or knowledge of why a test item is grammatical (Zoltán Dienes, Altmann, Kwan, & Goode, 1995). Some have pointed out that it is only relevant to equate conscious knowledge with control when knowledge is based on awareness of knowing, rather than guessing (Snodgrass, 2002).

Finally, with regards to the application of the PDP to motor statistical learning in the SRTT, it must be pointed out that inclusion and exclusion performance might merely reflect the triggering or inhibition of the procedural motor program that was learned, without a need for conscious insight into the sequence structure (Norman, Price, & Duff, 2006). Caution is therefore necessary when interpreting PDP results within the context of this paradigm.

1.5.1.4 Comparison of direct and indirect measures

Reingold & Merikle (1988) put forward the comparison between direct and indirect measures as a solution to the shortcomings of forced-choice tasks, such as their violation of the exclusiveness assumption. Whilst direct tasks explicitly instruct the participants to respond on the basis of knowledge which is relevant for the task, indirect tasks make no reference to the relevant dimension for task performance. Successful performance in the indirect task in the absence of knowledge demonstrated through the direct task is interpreted as evidence of unconscious knowledge. Since its development, the use of this technique has been advocated by several authors (Cohen, Ivry, & Keele, 1990; Reed & Johnson, 1994; Willingham et al., 1989) and has more recently been adapted for use with visual statistical learning (Turk-Browne et al., 2005; Kim et al., 2009).

Jimenez, Mendez, & Cleeremans (1996) used response times in an SRT task as an indirect measure of knowledge and a generation task as a direct measure. The authors found that participants were not able to express their knowledge in the generation task, despite they showed a response-time advantage to the training sequence in the SRT task, which was taken as evidence for unconscious knowledge. This is a demonstration of how implicit learning is inferred from this technique when the indirect measure is more sensitive to learning than the direct measure.

Despite its usefulness in attempting to resolve the issues around the poor sensitivity of verbal reports and forced-choice tasks, this technique raises an important methodological concern, which is that when performance in two tasks, such as, for example, a response-time task and a generation task, is being compared, the possibility that the two tasks are sensitive to, and therefore detecting different types of knowledge, and tapping into different abilities, cannot completely be excluded (Shanks & St John, 1994). For example, whilst the response-time task might tap into participants' learned motor programs for the training sequence, which facilitates their response to the on-screen cues, the generation task might require genuine recollection of that motor program, given that no on-screen cues are present. In this case, an observed dissociation between the direct and indirect task would not be a genuine reflection of the nature of knowledge but, rather a reflection of the fact that the two tasks tap into different types of abilities. It is therefore important for research using this approach to ensure that the direct and indirect tasks are sensitive to the same type of knowledge and, in case of an observed dissociation, to ensure that the experiment is able to rule out any other potential causes for that dissociation.

1.5.2 The phenomenological approach

The phenomenological approach defines consciousness in terms of the participant's subjective experience. Tests of conscious knowledge within the phenomenological approach, referred to as subjective tests, ask participants to report information about their own mental state (Dienes & Berry, 1997). While objective measures require participants to make a "worldly discrimination", that is, to show their ability to discriminate between features of the world, subjective measures require a "mental state discrimination", discriminating between their own mental states (Fu, Fu, & Dienes, 2008b). Within this approach, consciousness is defined as "knowing about knowing", and is therefore a metacognitive state. This proposal is referred to as Higher Order Thought (HOT) theory (Dienes & Scott, 2005a).

1.5.3 Combining objective and subjective approaches: the guessing and zero correlation criteria

Objective and subjective measures have been combined within the phenomenological approach, in order to obtain the best possible insight into the status of knowledge (Gaillard et al., 2014). The two measures put forward for this purpose, developed by Dienes and colleagues, are called the guessing criterion and the zero correlation criterion (Zoltán Dienes et al., 1995; Zoltan Dienes & Perner, 1999). These combine objective and subjective measures of awareness by assessing the relationship between test accuracy and confidence ratings, in the case of the zero correlation criterion, and test accuracy and knowledge attribution ratings, in the case of the guessing criterion. After exposure with the to-be-learned material, participants are administered a test of knowledge, such as a two-alternative forced-choice task and, on each forced-choice trial, knowledge attributions, such as rules (Zoltán Dienes & Scott, 2005a), memory, intuition and guess, are collected, as well as the participant's confidence, usually assessed on a scale 50-100 (Zoltán Dienes, 2004; Zoltán Dienes, 2007). According to the guessing criterion, unconscious knowledge is found when performance is above chance in trials in which participants claim that they are guessing. For the zero correlation criterion, unconscious knowledge is present when no relationship is observed between confidence and accuracy. This is assessed as the difference in confidence between trials in which the participants were correct and trials in which they were wrong (Dienes, 2004; Dienes, 2007). The guessing and zero correlation criteria have been suggested to be more sensitive to conscious knowledge than verbal reports, whilst at the same time retaining the qualitative advantages of verbal reports (Dienes, 2006; Zoltán Dienes, 2012).

The key limitation of subjective measures is individual bias (Destrebecqz & Peigneux, 2005a), that is, the fact that it is down to the individual participant to decide whether he/she thinks that they hold knowledge. The fact that different participants may have different confidence thresholds can make data difficult to interpret and compare across studies. For example, participants who might be biased towards claiming that they are guessing, might, in fact, have some small degree of awareness (Zoltán Dienes, 2007; Zoltán Dienes, 2004). Caution is therefore needed in their interpretation. It is also important to note that confidence ratings might not provide a realistic assessment of participants' conscious knowledge at the time of making their choice in a trial. It could be, for example, that increased perceptual fluency, leading to faster and easier processing, might cause participants to be confident in their choice in a given trial. This increased confidence could therefore be merely a product of increased fluency and, in actual fact, not correspond to conscious access to knowledge (Rünger & Frensch, 2010).

Aiming to improve subjective measures by minimising the problem of individual bias, a variety of subjective scales for the measurement of consciousness, such as the Perceptual Awareness Scale (PAS), confidence ratings, on a binary (Tunney & Shanks, 2003) or continuous scale, Post Decision Wagering (PDW) (Persaud, McLeod, & Cowey, 2007), and no-loss gambling (Zoltán Dienes & Seth, 2010) has been developed. These all successfully predict performance and can indicate the presence of task performance without awareness (Wierzchoń, Asanowicz, Paulewicz, & Cleeremans, 2012). However, see Szczepanowski (2010) for a contrasting opinion on post-decision wagering. Different scales tap into slightly different aspects of awareness, as well as interacting with stimulus difficulty and performance, reflecting the fact that our concept of consciousness is determined by the measures chosen to assess it (Sandberg, Timmermans, Overgaard, & Cleeremans, 2010). Research in recent years has moved towards an understanding of consciousness more as a gradual phenomenon (Mangan, 2001; Overgaard, Rote, Mouridsen, & Ramsøy, 2006; Norman et al., 2006; Norman, Price, Duff, & Mentzoni, 2007), something which should be reflected in any new scales which are developed.

When using the guessing and zero correlation criteria, it is also important to be aware of the type of conclusions that they allow us to draw with regards to implicit and explicit knowledge. Authors have distinguished between structural knowledge, that is, learning of the structure or rules of the to-be-learned material, and judgment knowledge, that is, knowing whether a test item is correct or grammatical (Mealor & Dienes, 2013). It is possible for structural knowledge to be unconscious when judgment knowledge is conscious. It is important to bear in mind that confidence ratings, as well as the PDP, only test the conscious status of judgment knowledge (Destrebecqz & Cleeremans, 2001; Fu et al., 2008b). Aiming to measure the conscious status of structural knowledge, (Dienes & Scott, 2005a) asked their participants to indicate, after each trial, whether their judgment was based on guessing, intuition, rules or memory. The authors hold that, while guessing and intuition attributions indicate unconscious structural knowledge, rules and memory indicate conscious structural knowledge. However, we suggest that the presence of structural knowledge cannot solely be inferred on the basis of rules attributions and, in order to ensure that conscious structural knowledge is indeed present, the participants would have to be asked to report these rules. Along the same lines, (Norman & Price, 2010) point out that caution is also needed with the interpretation of intuition attributions, as they can carry substantial ambiguity. In fact, these attributions might reflect a mixture of guess responses held with different levels of confidence, where neither judgement nor structural knowledge are conscious.

Finally, Overgaard, Koivisto, Sørensen, Vangkilde, & Revonsuo (2006) raised an interesting point to be considered with regards to subjective measures of conscious knowledge which require introspection. The authors provide electrophysiological evidence that, when participants are asked to attend to their own conscious mental states, this does not only influence post-perceptual processes but also earlier perceptual processes, which are pre-conscious. This yields the question whether subjective measures of conscious knowledge, through getting participants to attend to their own mental states, might influence the status of those mental states.

1.5.4 Implicit and explicit learning and their requirements for central resources

One approach to conceptualising the distinction between implicit and explicit learning proposes that these two types of learning can be distinguished on the basis of their requirements for central resources. Specifically, while explicit learning requires attentional resources to take place, implicit learning can proceed independently of them (Shanks, Rowland, & Ranger, 2005). Based on this view, it follows that a secondary task should be more likely to negatively impact explicit than implicit learning, a position that is in line with early proposals of two modes of learning, a u-mode learning, which is not available for verbal report and is not affected by the presence of a dual task, and an s-mode learning, which yields knowledge that is verbally accessible and negatively affected by a dual task (Hayes & Broadbent, 1988). In the context of sequential regularities learning this view has been adopted by a number of authors (Zoltán Dienes et al., 1995; Dienes & Scott, 2005b; Roberts & MacLeod, 1995; Waldron & Ashby, 2001; Ziori & Dienes, 2008) and is referred to as “the explicit intrusion hypothesis” (Jiménez & Vázquez, 2005) but, for an opposing view, see Shanks & Channon (2002a). Dual-task studies on sequential regularities learning have taken this approach and rely on a comparison of learning between a dual-task group and a single-task group These aim to investigate whether those tasks which are considered “implicit learning tasks” are negatively impacted by depleting attentional resources (Dienes & Scott, 2005; Hendricks, Conway, & Kellogg, 2013; Jiménez & Vázquez, 2005; Shanks & Channon, 2002; Shanks et al., 2005).

The majority of studies report a decrease in learning under dual- task conditions. These include, SRTT studies, where learning is reduced and there is a general increase in response times to the stimuli (Cohen & Poldrack, 2008; Coomans, Vandenbossche, & Deroost, 2014; Shanks & Channon, 2002; Shanks et al., 2005; Wierzchon, Gaillard, Asanowicz, & Cleeremans,2012) , triplet learning studies (Franco, Gaillard, Cleeremans, & Destrebecqz, 2014; Robinson & Sloutsky, 2013; Toro, Sinnett, & Soto-Faraco, 2005) and AGL studies (Dienes, Altmann, Kwan, & Goode, 1995). In AGL the presence of a dual- task has been found to have detrimental effects by impairing font sensitivity and chunk strength learning (Chang & Knowlton, 2004). The effects of a secondary task on regularities learning in the auditory domain have been less researched, although (Robinson & Sloutsky, 2013), using a Triplet Learning paradigm, found that a dual- task impaired statistical learning in visual but not auditory stimuli. In contrast to these results, some studies have reported intact learning under dual task conditions in AGL (Dienes & Scott, 2005; Hendricks et al., 2013) and SRTT (Cohen, Ivry, & Keele, 1990; McDowall et al., 1995). It is also important to point out that effects of divided attention on sequential regularities learning should be studied both at encoding and retrieval (Craik, Naveh-Benjamin, Ishaik, & Anderson, 2000). In fact, a given dual task, might not interfere with knowledge acquisition, but may be detrimental to knowledge expression, depending on the type of resources that it uses (Gaillard et al., 2012; Hendricks et al., 2013).

As Wierzchon, Gaillard, Asanowicz, & Cleeremans (2012) have noted, whether learning is observed or impaired in the presence of a secondary task can be determined by a number of variables such as the procedure of the primary task, the type of secondary task, the interactions between the primary and secondary task (Schumacher & Schwarb, 2009) and whether the two tasks are integrated (Schmidtke & Heuer, 1997; Halvorson, Wagschal, & Hazeltine, 2013). These factors may be responsible for the mixed results found in the literature, and are reviewed in detail in Wierzchon et al. (2012).

As the majority of the evidence points to the fact that tasks which are considered to require implicit learning are negatively impacted by the presence of a dual task, the attentional resources criterion to distinguish implicit from explicit learning has been suggested to be unsuitable (Shanks et al., 2005). Furthermore, there is evidence suggesting that learning is facilitated in the presence of attention. For example, in a triplet learning study which presented interleaved shape sequences in two different colours and instructed participants to only attend to one of the two colours, it emerged that recognition performance and response times in a subsequent rapid serial visual presentation task were better for attended than unattended shapes Turk-Browne et al. (2005). Findings are similar in the context of learning of an artificial language made of disyllabic words (Yu, Zhong, & Fricker, 2012) and the SRTT (Jiménez & Méndez, 1999), but see Kachergis, Yu, & Shiffrin (2010) for evidence that simultaneous learning of regularities in the visual and auditory modality may not need directed attention, although it benefits from it. Overall, these findings point to the importance of attention for sequential regularities learning to succeed.

The great majority of dual-task studies discussed so far have focused on a comparison of the amounts of knowledge acquired under dual- task and single- task conditions. Very few studies have actually measured how the presence of a dual task affects the type of knowledge acquired, implicit or explicit. In fact, based on the definition of implicit and explicit learning discussed above, there has been a tendency to assume that knowledge that survives dual- task conditions must be implicit in nature.

In a probabilistic SRTT, Shanks et al. (2005) compared performance in a single-task and dual-task group, who were performing a target counting task, and used a generation test under inclusion and exclusion instructions to assess the presence of implicit and explicit knowledge. The PDP showed that the dual- task and single-task groups did not differ in the amounts of explicit knowledge held. Both groups had some explicit knowledge of the sequence, indicated by a greater inclusion than exclusion score.

Wierzchon et al. (2012) compared SRTT performance in a single-task and a dual-task group. This latter group was required to perform a Random Number Generation (RNG) task, generating a random digit on each key press of the reaction time task. Explicit and implicit knowledge were assessed through PDP. There was a general impairment of generation performance which was not specific to inclusion or exclusion scores, leading the authors to conclude that it was related to general attentional load. When using a less demanding version of the RNG task, where participants had to generate a number every fourth key press, no specific impairment of generation performance was found. Rather, higher inclusion than exclusion scores across both dual-task and single-task conditions indicated that explicit knowledge of the sequence was present. This suggests that it is possible for explicit knowledge to develop in the presence of a low-demand secondary task.

In an AGL experiment, Dienes & Scott (2005) compared the effects dual- task and single- task conditions on grammaticality classification performance for “memorise” instructions (participants were asked to memorise the training strings) and “rule-search” instructions (participants were instructed to try to uncover the underlying grammar rules. The rule search instructions combined with a secondary task during the training phase (RNG) influenced classification performance when this was associated with conscious structural knowledge but not when it was associated with unconscious structural knowledge. They suggested that, whilst divided attention depletes resources dedicated to deliberating about rules, it does not affect the development of familiarity.

Further investigations of the amounts of implicit and explicit knowledge produced under dual-task conditions should be conducted before drawing any firm conclusions. The evidence gathered so far, however, suggests that it is possible for explicit knowledge to develop despite the presence of a dual-task, and that this depends on the amount of resources required by the secondary task, against the suggestion that, whilst implicit knowledge is unaffected by a secondary task, explicit knowledge is negatively affected.

1.5.5 Measuring implicit and explicit knowledge: the current state of play

As emerged from this section, the operationalisation of conscious knowledge intended as awareness is extremely difficult, and research is far from reaching a consensus on the best measure (Gaillard, Vandenberghe, Destrebecqz, & Cleeremans, 2006). Because different operationalisations of awareness have led to the development of different experimental measures, which can at times conflict with each other, results are not easily comparable across tasks. In fact, not only the type of learning involved, but also the way that knowledge is acquired may be different in different tasks. As a consequence of this situation, the amount of evidence obtained for implicit or explicit learning may vary depending on the Sequential Regularities Learning task used and the measure of awareness chosen (Seth et al., 2008).

To add to this already complex situation is the fact that the measures of conscious knowledge discussed in this section were developed with specific Sequential Regularities Learning tasks in mind, which complicates the picture when attempting to make comparisons between studies in this field. This also means that we lack information on the suitability of these measures for certain tasks. For example, the PDP has mainly been applied in the context of motor learning and its use in the context of forced-choice tasks is very limited indeed. As the PDP results obtained within motor statistical learning may be, at least partly, influenced by procedural motor learning (Norman et al., 2006), their applicability to non-motor learning paradigms is limited. Similarly, the guessing and zero correlation criteria are mainly used in the field of Artificial Grammar Learning and research in this field would benefit from information on their applicability to other Sequential Regularities Learning paradigms.

There is also the question of the modality in which the learning takes place. The literature reviewed in this section focuses mainly on motor learning, therefore using visually-presented stimuli, or artificial grammar learning, which also involves visual stimulus presentation. Although a limited amount of triplet learning work has been carried out in the visual modality, there is a scarcity of studies assessing the available measures of conscious knowledge in the auditory modality.

Consciousness is a highly complex phenomenon, which, as we have seen in this section, has been proposed to possess a number of different functions. For this reason, together with other authors (Gaillard et al., 2006), we argue in favour of using a combination of objective and subjective measures, which is not only more likely to capture the different aspects of this construct, but also useful in terms of the two approaches operating mutual control.

1.6 Implicit and explicit learning in sequential regularities learning research

1.6.1 The roles of implicit and explicit knowledge in sequential regularities learning

Although Sequential Regularities Learning tasks have traditionally been considered implicit learning tasks, when the question of the status of knowledge is examined more closely, it appears that both implicit and explicit knowledge are involved. Not much research has systematically measured the type of knowledge acquired in these paradigms, and drawing firm conclusions is made more difficult by the use of different measures of conscious knowledge, and different Sequential Regularities Learning paradigms, which limits our ability to make direct comparisons between studies. When focusing on those studies which have attempted to draw a distinction between implicit and explicit knowledge, the body of work appears to suggest that there are a number of variables which affect the amounts of implicit and explicit knowledge observed in this type of learning. In order to identify influences on implicit and explicit learning, the following section will be organised on the basis of the variables identified in the literature. For the purpose of this thesis, this brief review will solely focus on studies which shed light on the question of implicit and explicit knowledge in sequential regularities learning, therefore excluding research on implicit and explicit knowledge which has not used our paradigms of interest.

1.6.2 Influences on implicit and explicit knowledge

1.6.2.1 Task instructions

A number of studies in Sequential Regularities Learning has investigated the effects that incidental learning conditions, when there is no intention to learn, and intentional learning conditions, when participants are specifically instructed to memorise the training stimuli, have on the amount of learning Some studies have extended this question to whether learning is implicit or explicit in these conditions. Incidental instructions are claimed to recruit more implicit processes than intentional instructions (Stevens, Arciuli, & Anderson, 2014). Evidence from AGL indicates greater use of strategies such as feelings of familiarity (Scott & Dienes, 2008) similarity- based knowledge (Opitz & Hofmann, 2015) and implicit knowledge attributions in implicit learners (Dienes & Scott, 2005). In contrast, when given explicit instructions, participants seem to use rule- based knowledge (Opitz & Hofmann, 2015). Explicit instructions seem to encourage the use of explicit learning strategies in learners, which is in line with ERP evidence suggesting larger grammaticality- related effects in SRTT studies for intentional than incidental learners (Rüsseler, Hennighausen, Münte, & Rösler, 2003; Baldwin & Kutas, 1997; Ferdinand, Mecklinger, & Kray, 2008) and a greater relevance of errors for intentional learners (Rüsseler, Kuhlicke, & Münte, 2003a).

This could explain the better performance found for intentional than incidental learners, despite sequence learning takes place under both conditions. This is documented in AGL, (Scott & Dienes, 2008), in the SRTT (Baldwin & Kutas, 1997; Ferdinand et al., 2008; Jimenez, Mendez, & Cleeremans, 1996; Jiménez, Vaquero, & Lupiáñez, 2006; Stefaniak, Willems, Adam, & Meulemans, 2008), and in other statistical learning paradigms such as cross-situational word learning (Hamrick, Philllip, Rebuschat, 2012). Fewer studies have found no difference in the amounts of learning between incidental and intentional groups of participants in the SRTT, a finding which is possibly due to methodological differences in these studies (Rüsseler, Kuhlicke, & Münte, 2003; Song, Howard, & Howard, 2007a; Sanchez & Reber, 2013), AGL (Dienes & Scott, 2005), and TL (Arciuli, von Koss Torkildsen, Stevens, & Simpson, 2014).

Findings about the effects of task instructions are consistent with the proposal that there are two different systems for implicit and explicit learning: while implicit learning consists of passively aggregating information about events which co- occur, explicit learning is focused, and guided by hypothesis testing (Hayes & Broadbent, 1988). From a methodological point of view, it is important to note that the procedure for many of these studies involves informing participants, between the exposure and the test phase, that the experimental stimuli contain statistical regularities. This could potentially introduce some explicit knowledge, therefore biasing the measurement of the status of knowledge carried out during the test phase of the experiment. Future research should work on this methodological challenge, aiming to discover whether there is a way to test knowledge of sequential regularities entirely implicitly.

1.6.2.2 Probabilistic or deterministic sequences

Some studies have compared implicit and explicit knowledge in deterministic and probabilistic sequences. Whilst a deterministic sequence is fixed, meaning that each element in the sequence will follow the previous element, or previous elements, 100% of the time, probabilistic Statistical Learning tasks use noisy sequences, in which the transitions from one element to another follow a fixed sequence, for example, only 80% of the time, and the remaining events are not part of the fixed sequence. The claim that knowledge is more likely to be implicit in a noisy sequence (Cleeremans & Jimenez, 1998; Jimenez 2003; Schvaneveldt & Gomez, 1998) has been confirmed by SRTT findings that conscious knowledge is present in deterministic and less noisy sequences (when the sequence is followed on more than 85% of trials) (Fu et al., 2008b; Wilkinson & Shanks, 2004a), while knowledge for more noisy sequences seems to be implicit (Fu et al., 2008b).

1.6.2.3 The interaction between task instructions and deterministic/ probabilistic sequences

Only few studies, and only limited to the SRTT, have compared the effects of manipulations of task instructions for probabilistic and deterministic sequences. Findings suggest that the response-time advantage that explicit learners have over implicit learners is lost in probabilistic sequences (Jimenez et al., 1996b; Jiménez et al., 2006; Stefaniak et al., 2008), possibly due to their higher unpredictability. In both probabilistic and deterministic sequences, intentional learners hold more explicit knowledge than incidental learners (Jiménez et al., 2006), suggesting that the use of explicit strategies can make sequence knowledge more explicit, despite the higher unpredictability of probabilistic sequences. However, there is some contradictory evidence suggesting that explicit learners show explicit knowledge in probabilistic but not deterministic sequences, possibly due to automaticity in deterministic sequences making it difficult to perform the exclusion task (Jimenez et al., 1996b; Jiménez et al., 2006; Stefaniak et al., 2008). It would be necessary to gather evidence from non- motor sequential regularities tasks, where automaticity does not play a role. It may be that different results are produced by a different implementation of PDP, for example, as a 2-Alternative Forced Choice Task instead of a generation task.

1.6.2.4 Adjacent versus non-adjacent dependencies

Given its importance for understanding learning of regularities in high- level domains such as language and music, the extent to which participants are able to acquire dependencies between elements which are not adjacent within a stimulus stream has been investigated using artificial language streams (Gomez, 2001; Newport & Aslin, 2004; Onnis, Monaghan, Richmond, & Chater, 2005; Li, Jiang, Guo, Yang, & Dienes, 2013) musical sequences (Creel et al., 2004; Kuhn & Dienes, 2005) and shape sequences (Turk-Browne et al., 2005). There is evidence that it is possible for participants to learn up to third-order dependencies (for examples using the SRTT, see Cleeremans & McClelland (1991) and Remillard & Clark (2001)), although it seems that there are some necessary conditions that need to be in place for learning of non- adjacent dependencies to occur (for examples of these, see Newport & Aslin (2004), Creel et al., (2004) and Gomez, (2001)) and some research suggests that joint attention to the non-adjacent elements is needed for learning to occur (Pacton & Perruchet, 2008).

Very little research has been directed to assessing whether learning of local and non- local dependencies occurs through implicit or explicit learning processes. Participants' ability to learn non- local dependencies could be seen as evidence against chunking theories of knowledge acquisition, suggesting that knowledge is acquired in the form of explicit chunks belonging to the exposure stream (Kuhn & Dienes, 2008). Based on this, it could be hypothesised that knowledge of adjacent elements is held explicitly and knowledge of non-adjacent elements is held implicitly, because it cannot be acquired in the form of chunks. This hypothesis only finds limited support in the available literature: Kuhn & Dienes (2005) found that knowledge of the diatonic inversion rule, a musical rule based on non-local dependencies, was held implicitly, without awareness of the rule.

Artificial grammars which contain distant dependencies have been found to induce a greater use of rule- based knowledge attributions compared to local dependencies in a regular grammar (Opitz & Hofmann, 2015), where strategies based on similarity between test strings and training strings are efficient for performance in the 2AFC task (Kinder & Assmann, 2000; Lotz, A., Kinder, 2006). Based on this evidence, it seems that the knowledge acquisition strategies applied are flexible depending on the specific material to be learned. Similarity- based strategies, such as chunking, used for the learning of local dependencies, could be argued to lead to explicit knowledge. The question of what form is taken by knowledge of non- adjacent dependencies and, specifically, whether it is at all possible to acquire knowledge of non-adjacent elements in the form of chunks, is still outstanding. Further investigations, using a variety of sequential regularities learning paradigms, and incorporating an assessment of implicit and explicit knowledge, would be needed to answer this question.

1.6.2.5 Interaction between adjacent/ non-adjacent dependencies and task instructions

It seems that task instructions have an effect on the knowledge that can be acquired in sequential regularities learning. There is evidence indicating that, while incidental learners tend to acquire chunks of adjacent elements, such as bigrams or trigrams, intentional learners are able to acquire knowledge of grammar rules. Knowledge of both rules and chunks is found to be explicit (Kuhn & Dienes, 2006; Johnstone & Shanks, 2001). Based on this evidence, it could be hypothesised that participants' tendency is to chunk neighbouring elements within the stimulus stream, unless task instructions direct them to a different strategy. Some have suggested that, whenever an effortless and fast similarity-based process can guarantee sufficient accuracy, participants use this criterion for performance in an AGL task (Domangue et al., 2004) but can make use of rule- based processes when the task demands require it (Nokes

& Ash, 2010). This finds support in claims that participants only learn the type of relations that they have to actively process (Pierre Perruchet, 2008).

1.6.2.6 Amount of training

Cleeremans & Jimenez (2002) put forward the idea that in sequence learning the representations produced by unconscious knowledge can influence performance but are too weak to support explicit knowledge, and that knowledge becomes more available to conscious control as training progresses. This proposal has found some empirical support in SRTT studies. Implicit knowledge in low- training groups is found to become explicit in high- training groups (Remillard & Clark, 2001; Fu, Dienes, & Fu, 2010b; Fu et al., 2008b), but see Wilkinson & Shanks (2004b) for contrasting results. It is possible that training promotes the learning of explicit chunks of the exposure stream due to repetition of the sequence of elements.

In AGL, increased training is found to result in more stimulus- specific knowledge (Cleeremans & Jimenez, 2002), a finding consistent with the idea of knowledge becoming more explicit with extended practice (Ziori & Dienes, 2012; Goujon, Didierjean, & Poulet, 2014). Longer training is also found to produce an increase in rules knowledge and a decrease in similarity-based strategies (Fletcher, Buchel, Friston, J, & Dolan, 1999). While similarity- based learning is considered to be a fast process, rule learning is laborious and slow but yields high levels of grammatical knowledge (Domangue et al., 2004).

1.6.2.7 Task speed

The effects of task speed have been investigated by altering the Response Stimulus Interval (RSI), that is, the interval between the participants’ response and presentation of the next stimulus. In the SRTT knowledge is found to be implicit at a short RSI (0 msec) and explicit at a longer RSI (250 msec) (Cleeremans, 2003; Destrebecqz & Cleeremans, 2001). It is possible that longer RSIs allow time for conscious stimulus representations to form (Cleeremans, 2003;

Destrebecqz & Cleeremans, 2001; Miyawaki, 2006). RSIs could also be used to predict the next stimulus (Miyawaki, 2006), therefore allowing participants to engage in more explicit learning strategies. In line with these suggestions, there are also findings based on the visual triplet learning paradigm which suggest that short stimulus presentation times may limit the amount of explicit knowledge that is developed (Arciuli, von Koss Torkildsen, Stevens, & Simpson, 2014). Similar proposals have been based on AGL evidence that unconscious knowledge is elicited rapidly while conscious knowledge needs time to form (Mealor & Dienes, 2012). However, for contrasting results see Wilkinson & Shanks (2004b) who found conscious knowledge in the SRTT at an RSI of 0 msec. Future research should compare explicit and implicit knowledge at different task speeds for the auditory and visual modalities.

1.6.2.8 Transfer of knowledge between and within modalities

A question in sequential regularities learning is whether the acquired knowledge can be transferred to stimuli with different surface properties, or in a different modality, to that of the encoding stimuli. This is related to the question of what is learned and whether this learning is domain-general, that is, applicable to multiple stimulus types and modalities, or domain specific, that is, tied to the specific surface structure and modality of the stimuli. [2] In fact, successful transfer performance has been attributed to the abstractedness of the representations acquired during training, which are considered to be domain- general and not tied to the perceptual properties of the stimuli (Dienes, Altmann, & Gao, 1999) and can therefore apply to stimuli which maintain the same structural relations as during training but different surface properties, such as a different modality of presentation, in the case of cross-modal transfer (Yildirim & Jacobs, 2015). In the area of motor learning, research suggests that within-modality transfer of knowledge from a sequence to its mirror sequence (Grafton, Hazeltine, & Ivry, 2002) or transfer of knowledge to a different hand used for response (Verwey & Clegg, 2005) are both possible. This has been taken as evidence for abstract motor sequence

[2] The question of domain generality and domain specificity in sequential regularities learning is an important topic of debate within this field, as shown by a number of comprehensive reviews on the subjects, such as (Conway, Christopher M.; Pisoni, 2009), (Frost et al., 2015) and (Krogh et al., 2013).

representations which are effector-independent. Evidence of successful transfer in the non-motor domain comes mainly from AGL studies of within- modality (Reber, 1969; Mathews et al., 1989) and between- modality transfer (Altmann, Dienes, & Goode, 1995; Dienes et al., 1999), as well as visual triplet learning research, indicating that the learning of visual triplets sequentially presented during the exposure phase can successfully be applied even if the mode of presentation is disrupted, by presenting the three shapes in a triplet simultaneously, and in a different sequential order (Turk-Browne & Scholl, 2009). More recent evidence also points to the possibility of between-modality transfer in statistical learning, using a transition matrix paradigm (Durrant, Cairney, & Lewis, 2016).

Despite this evidence, the idea of transfer due to domain- general abstract representations has been challenged by research which has found no transfer of knowledge (Christiansen, Christiansen, Conway, & Conway, 2006; Bly, Carrion, & Rasch, 2009) and by claims that learning of sequential regularities is modality- specific (Conway & Christiansen, 2005, 2009; Emberson, Conway, & Christiansen, 2011; Mitchel & Weiss, 2014). Indeed, the evidence indicates that transfer within modality, that is, transfer of knowledge between stimuli with the same statistical structure but different surface properties, such as different colour or shape, is stronger than transfer across modalities, for example, transfer of knowledge from auditory stimuli to visual stimuli with the same statistical structure.

Alternative ways of explaining what makes knowledge transfer possible have been suggested. Successful transfer performance could be attributable to the presence of repetitions in the input stream (Gomez, Gerken, & Schvaneveldt, 2000; Scott & Dienes, 2010; Lotz & Kinder, 2006) or learning of whole fragments in the training sequence (Redington & Chater, 1996). Furthermore, cues present in the input stream could influence grammaticality decisions about the transfer stream (Tunney & Altmann, 1999). It has also been suggested that transfer across modalities can only occur when it is possible to use explicit inferences during test (Newell & Bright, 2002). These could facilitate associations between the learned exposure material and the different test material.

In terms of the roles of implicit and explicit knowledge in transfer, it could be hypothesised that, as transfer of knowledge of explicit chunks of the exposure sequence is not possible, transfer performance must be supported by implicit knowledge. Some research has proposed that the knowledge transferred is indeed implicit in nature (Durrant et al., 2016; Tanaka & Watanabe, 2014; Scott & Dienes, 2010). However, to date there is no consensus over whether genuine transfer of knowledge is possible (Vouloumanos et al., 2012). It seems that more evidence will need to be gathered before reaching any firm conclusions.

1.6.2.9 Knowledge consolidation

The majority of studies on sequential regularities learning has focused on an immediate assessment of knowledge and comparatively very few have examined the effects of a consolidation period on learning. Much of the work on consolidation in the field of statistical learning has focused on the SRTT (Janacsek & Nemeth, 2012). Motor learning in the SRTT is found to improve after a period of consolidation (Nemeth et al., 2010; Rieth, Cai, McDevitt, & Mednick, 2010; Song, Howard, & Howard, 2007) with some evidence for sleep- specific benefits to motor learning (Dehkordi, Abdoli, Zadeh, & Ashayeri, 2014; Csabi, Varszegi-Schulz, Janacsek, Malecek, & Nemeth, 2014). Auditory SL is also thought to benefit from sleep- dependent consolidation, with a specific role of Slow Wave Sleep (Durrant, Taylor, Cairney, & Lewis, 2011b; Durrant et al., 2016) although some claim that SL is consistent over time, with no specific beneficial role of sleep (Arciuli & Simpson, 2012a; Kim et al., 2009). It has also been suggested that sleep–dependent consolidation of implicit knowledge is only possible when contextual associations can be made during learning (Spencer, Sunm, & Ivry, 2006). For a review of the evidence regarding sleep and memory consolidation see Rasch and Born (2013). A relevant question is whether a period of consolidation can affect the amounts of implicit and explicit knowledge. Evidence based on the SRTT task suggests that sleep facilitates the conversion of implicit knowledge into explicit knowledge (Drosopoulos, Harrer, & Born, 2011; Fischer, Drosopoulos, Tsen, & Born, 2006). The Unconscious Thought Theory suggests that unconscious processing which takes place in the interval between the acquisition of knowledge and the test phase can benefit performance in the test (Dijksterhuis, Bos, Nordgren, & van Baaren, 2006). There is AGL evidence in favour of this proposal, although this unconscious knowledge does not translate into conscious knowledge (Andy David Mealor

& Dienes, 2012). More research is needed to identify the benefits of consolidation in the learning of regularities, its effects on implicit and explicit knowledge, and how this differs between motor and non-motor learning and between different experimental paradigms.

1.6.3 Influences on implicit and explicit knowledge: conclusions

This very brief overview of variables which have been shown to affect implicit and explicit knowledge in Sequential Regularities Learning aimed to show that, despite the common assumption that knowledge generated from this type of learning is implicit, there is evidence for both types of knowledge, implicit and explicit, and that manipulations of a number of variables have been shown to affect the amounts of implicit and explicit knowledge observed. However, based on the literature reviewed, it is difficult to make generalisations and draw conclusions on this subject, due to the use of different Sequential Regularities Learning paradigms and of different measures of conscious knowledge in different studies, which has led to contrasting results. More work is needed on statistical learning, intended as learning which is based on the extraction of transition probabilities over time and, within this, a comparison of methods for measuring conscious knowledge and their suitability in both the visual and auditory modality. Such systematic work will allow to shed light on the question of implicit and explicit knowledge in visual and auditory statistical learning.

1.7 This Thesis

The previous sections have discussed the question of implicit and explicit knowledge in Sequential Regularities Learning, pointing to the available evidence to date and highlighting the theoretical and methodological challenges that researchers have encountered in this field of study. A complex picture emerged, partly complicated by the fact that there are no systematic investigations on how different measures of conscious knowledge perform with the same Sequential Regularities Learning paradigm, making it difficult to compare results across studies. Methodologically, determining whether knowledge is implicit or explicit has presented several challenges, and the dispute as to the best method for measuring conscious knowledge is far from settled (Gaillard et al., 2006; Timmermans & Cleeremans, 2014). The present thesis aims to address this issue by adopting a novel use of the Process Dissociation Procedure in the context of a forced-choice task in combination with the guessing and zero correlation criteria. Our ultimate objective is to aim to clarify if, and in which sense, we can say that the knowledge acquired in statistical learning is implicit or explicit.

In the field of language learning, authors have pointed to the necessity to assess the awareness of the acquired knowledge (Rogers, Révész, & Rebuschat, 2016; Rebuschat & Williams, 2012; Rebuschat & Williams, 2008), as it is believed that understanding the role of conscious and unconscious learning is a crucial step in the understanding of language acquisition (Guo et al., 2011). Practical applications also lie within the field of music. There is evidence, for example, that implicit learning plays an important role in the acquisition of complex characteristics of melody, harmony, timbre and rhythm (Rohrmeier & Rebuschat, 2012). Given the lack of agreement as to suitable measures of implicit and explicit knowledge, a thorough understanding of explicit and implicit knowledge in laboratory-generated stimuli is a first necessary step to eventually facilitate the understanding of how implicit and explicit knowledge work in these real-life domains.

Previous sections in this chapter have also highlighted the fact that most of the literature on implicit and explicit learning is based on AGL and the SRT task, whereas comparably less work has been carried out on Statistical Learning. We argue, together with other authors (Krogh, Vlach, & Johnson, 2013), that, given the importance of transition probabilities for the prediction of upcoming events on the basis of previous ones, more work should be done using statistical learning paradigms. It is also important to note that statistical learning paradigms such as the transition matrix (Durrant et al., 2011b; Durrant, Cairney, & Lewis, 2013b) have high flexibility in terms of the types of stimuli that they are able to generate, for example, first or second order condition statistics, or control over the level of difficulty of the stimuli. These paradigms are therefore the most promising with regards to generalising conclusions to more complex stimuli such as natural language or music. We plan to address this research gap by focusing specifically on statistical learning paradigms in this thesis.

Finally, statistical learning as applied to language learning was developed primarily for study in the auditory modality. However, visual paradigms have also served an important purpose, as they were originally intended to shed light on whether SL is a domain-general learning mechanism that operates regardless of modality (Kirkham et al., 2002; Bulf, Johnson, & Valenza, 2011). This thesis will study SL in the visual and auditory modalities in parallel, to address the question of potential differences in implicit and explicit knowledge and to assess the applicability of the available measures of conscious knowledge to the two modalities.

The plan of work for this thesis is as follows:

Chapter 2 and Chapter 3 will test implicit and explicit knowledge in the transition matrix paradigm and the triplet learning paradigm, respectively, These two chapters aim to establish the suitability of our chosen measures of conscious knowledge, whether knowledge is prevalently implicit or explicit, whether there are any differences between the auditory and visual modalities and, finally, whether there are any differences between adults and children in the use of implicit and explicit knowledge. Chapter 4 will test the usefulness of direct and indirect measures of knowledge to shed light on implicit and explicit processes, and will compare these between adults and children. Chapter 5 will investigate the effects of speed of stimulus presentation on implicit and explicit knowledge and Chapter 6 aims to validate and extend our previous work by looking into the electrophysiological correlates of implicit and explicit knowledge.

Such systematic work will allow to bring greater clarity to outstanding methodological questions in the field regarding the suitability of behavioural measures of conscious knowledge, and theoretical questions as to whether, or under which conditions, knowledge in Statistical Learning can be defined as implicit or explicit.

Chapter 2 Transition matrix in the visual and auditory modalities

2.1 Introduction

Statistical learning has traditionally been considered a form of implicit learning (Pierre Perruchet & Pacton, 2006). Within this thesis, we aimed to test this assumption, and develop an understanding of the type of knowledge which is acquired as a result of statistical learning, implicit or explicit. We consider the ecological validity of laboratory stimuli to be of paramount importance in this work, and suggest that the transition matrix paradigm has been under-used in the literature to date. In fact, the field of statistical learning would benefit from more work on the transition matrix paradigm, specifically, research on the type of knowledge acquired, implicit or explicit, as a result of learning the statistical structure of stimuli generated through transition matrix. A transition matrix is a matrix which determines the probability of transitioning from one element to another within a sequence based on the preceding element(s) (Durrant et al., 2011a; Durrant et al., 2013a; Durrant et al., 2016). In the example of a second-order conditional sequence, the probability of occurrence of each element within the sequence is determined on the basis of the previous two elements. Within a transition matrix, any stimulus has a certain degree of association to other stimuli. This is a highly flexible method for the generation of statistically structured stimuli, in that it allows manipulation of the order of the transition probabilities and of the level of noise within the stimuli, which affects the difficulty of the to-be-learned material. It therefore has high ecological validity in the study of statistical learning.

Defining the boundaries of the statistical learning ability is of essence in order to develop a thorough understanding of it (Krogh et al., 2013). Therefore, there is a need to determine what can be learned and what cannot be learned and in which modality. We know from previous transition matrix work in the auditory modality (Durrant et al., 2011a; Durrant et al., 2013a) that, after being exposed to a long probabilistic tone sequence, participants are able to discriminate 18-tone “structured” test sequences which share the same statistical structure as the exposure stream from “unstructured” test sequences which are generated randomly. This is taken as evidence that the transition probabilities between elements in the exposure stream have been learned (Durrant et al., 2011a; Durrant et al., 2013a). However, no work has been carried out on transition matrix stimuli in the visual modality, except for one experiment which studied cross-modal transfer between the visual and auditory modality (Durrant et al., 2016). The aim of this study, however, was to test transfer of knowledge from the statistical structure of transition matrix stimuli learned in the auditory modality to test sequences implemented in the visual modality, and therefore did not involve learning in the visual modality. It is necessary to explore the potential of transition matrix in the field of visual statistical learning, as this is potentially a promising paradigm for the study of sequentially-presented regularities in the visual modality. The present study addressed this gap by implementing the symbolic stimuli generated through transition matrix as visual shapes which have been previously used in visual statistical learning research.

For what concerns the status of the acquired knowledge, at present, there is virtually no research investigating explicit and implicit knowledge within an auditory or visual transition matrix paradigm. The transition matrix work mentioned thus far has used this paradigm for the purpose of assessing implicit extraction of statistical regularities, implicit learning, intended as learning which occurs without intention to learn (Durrant et al., 2011a; Durrant et al., 2013a). However, no actual testing of the status of the acquired knowledge was carried out in these studies. This is the first experiment addressing this gap and a necessary first step toward systematic comparison of the two input modalities. In fact, our aim was to develop a method which allows the measurement of implicit and explicit knowledge of transition matrix stimuli in the visual and auditory modalities, so that the two can be investigated in parallel. This could be a very important contribution to the field of statistical learning both from a methodological and theoretical perspective.

For this purpose, we tested the use of two current measures of implicit and explicit knowledge: the Process Dissociation Procedure (PDP) and the guessing and zero correlation criteria. The PDP has never been used to assess the status of knowledge of transition matrix stimuli. Its main use in the field of statistical learning has been in the context of the SRTT, where inclusion and exclusion instructions have been applied to a generation task (Bischoff-Grethe et al., 2004; Norman & Price, 2010; Fu et al., 2008a; Fu et al., 2013). After motor training with the repeating sequence, under inclusion instructions participants are asked to reproduce the training sequence by using the same response keys as during training, and under exclusion instructions they are asked to produce a sequence different from the training sequence. Findings of both implicit and explicit knowledge are not uncommon in this implementation of the PDP (Fu et al., 2008a; Fu et al., 2013), although caution should be used when generalising these findings to non-motor paradigms, as there is a possibility that generation performance, as it occurs through the same keys which were used during training, might be influenced by implicit motor programs (Norman et al., 2006).

The advantage of a generation task is that it taps into participants' explicit recollection, and therefore it could be argued that it is a more genuine measure of their sequence knowledge. However, its implementation in the context of visual and auditory stimuli is not feasible due to practical methodological constraints, such as getting participants to produce tones or shapes. This is particularly true for complex or longer test stimuli which are difficult to reproduce, or generate, by participants as part of a generation task. It was therefore necessary to develop a method for the use of PDP in the context of a forced-choice task. One experiment has used the PDP to study auditory triplet learning, using two artificial languages (Franco et al., 2011a). Participants were presented with one artificial word and were asked to answer "yes" if this was a word from the training language and "no" if it was a non-word under inclusion instructions, and the reverse under exclusion instructions. The authors found that learning of the two languages also led to control of the expression of the acquired knowledge. The present experiment is the first to implement the PDP in the context of a forced-choice task using tone stimuli. We also used confidence and knowledge attribution ratings on each forced-choice trial for the purpose of the guessing and zero correlation criteria. We expected this combination of measures of conscious knowledge to further our understanding of their validity. In fact, we were specifically interested in whether the three measures yield converging results.

As we were interested in studying the developmental course of statistical learning, and in potential differences between adults and children in the use of implicit and explicit knowledge, this study included a sample of adults and a sample of children. Based on previous transition matrix work (Durrant et al., 2011b; Durrant et al., 2013a; Durrant et al., 2016), we expected adult participants to acquire knowledge in the auditory transition matrix task. In visual triplet learning experiments, adults have been found to be able to segment shape triplets from a continuous stream (Bertels, Franco, & Destrebecqz, 2012b; Bertels et al., 2015a; Fiser & Aslin, 2002a; Fiser & Aslin, 2001; Turk-Browne et al., 2005; Turk-Browne & Scholl, 2009; Turk-Browne, Scholl, Chun, & Johnson, 2009). The statistically-structured stimuli in this study were entirely based on second-order transition probabilities, therefore each element within the sequence was entirely predictable based on the previous two elements (Durrant et al., 2011b; Durrant et al., 2013a). As zero and first-order dependencies provide no useful information in this context, in the same way as Durrant et al. (2011b) and Durrant et al. (2013a), their probabilities were deliberately controlled in these stimuli. Studies based on the SRTT also often make use of second-order conditional sequences. These sequences are divisible into three-element units in which the first two elements entirely predict the third, and which are overlapping, in the sense that the third element of one triplet is also the second element of another and the first element of a triplet after that. For this reason, some authors have referred to the three-element units within these second-order sequences as “triplets” (Fu et al., 2013). A generation task can be implemented on the basis of these triplets, where the first two elements in a triplet are primed and participants are asked to produce the third element (Fu et al., 2013). We therefore know from the literature that participants are able to learn three-element units from a continuous stream. Findings of successful test performance in the transition matrix studies carried out so far are taken to mean that participants have acquired knowledge of the transition probabilities within the exposure stream (Durrant et al., 2011b; Durrant et al., 2013b; Durrant et al., 2016). Based on this assumption, we reasoned that our participants should be able to discriminate statistically-structured three-element test sequences from unseen test sequences in the 2AFC task.

Sensitivity to statistical regularities is an ability that develops early, and its presence in both infants and children is well documented by existing research. Evidence from early studies exploring the auditory domain comes from statistical learning research using artificial speech. Infants as young as 8 months (Saffran et al., 1996), as well as children (Saffran et al., 1997), are found to be able to successfully segment word units from the artificial speech stream.

Learning in the auditory domain is not only limited to input stimuli which closely resemble language. Saffran et al., (1999) also implemented their artificial speech stimuli as tones to form “tone words”, and found that 8-month-old infants were successfully able to segment the “tone words” from the input stream, replicating the findings previously obtained by these authors using artificial speech stimuli.

Although early research in this area has focused on the auditory domain, due to its usefulness in the study of language acquisition in children and the closer resemblance of the laboratory-developed auditory stimuli to natural language, research on children and infants is not limited to the auditory modality. The ability to learn the statistical structure of shape stimuli presented in recurring pairs, tested through a habituation paradigm, was found in new-borns, as young as 1-3 days (Bulf et al., 2011). Similarly, 2-, 5-, and 8-month-old infants were found to be able to learn the statistical structure of coloured shapes which were presented in a predictable pattern (Kirkham et al., 2002). Findings of learning of sequential regularities in visual stimuli at such a young age have been taken as support for the idea that statistical learning is a domain-general mechanism that applies to different modalities (Bulf et al., 2011; Kirkham et al., 2002). The visual triplet learning paradigm, using visual triplets made up of cartoon characters, has been tested with children, who are found to acquire the triplet structure, similarly to adults (Arciuli & Simpson, 2011; Arciuli & Simpson, 2012b). Evidence to date seems to suggests that performance in statistical learning tasks, not only for sequentially-presented regularities, but also spatially-presented, follows a developmental trajectory, in that it improves with age (Vaidya, Huger, Howard, & Howard, 2007; Arciuli & Simpson, 2012b; Arciuli & Simpson, 2011), although there is also some evidence to the contrary coming from comparisons of performance in different age groups in the SRT task (Karatekin, Marcus, & White, 2007) and AGL (Witt, Puspitawati, & Vinter, 2013).

Similar to research on adults, not much is known about explicit and implicit knowledge in statistical learning in children, and no work has been carried out which investigates this question using a transition matrix paradigm. One SRTT study on the effects of explicit task instructions on performance and status of knowledge compared benefits of explicit instructions on different age groups (Thomas & Nelson, 2001). The authors assessed sequence awareness through a generation task, which found that older children developed more explicit awareness as a result of explicit instructions than younger children. These results might suggest that the development of explicit knowledge follows a developmental trajectory. Other studies, however, seem to suggest the opposite. For example, Weiermann & Meier (2012) tested children, adults and older adults on a variant of the SRTT which involved speeded classification of coloured pictures which appeared in a specific sequence. They assessed explicit sequence knowledge through a generation task which asked participants to verbally generate six elements of the picture sequence, and a recognition test which included confidence ratings. Children were not found to differ from adults in the amount of explicit knowledge that they showed and only those children who had acquired explicit sequence knowledge displayed a response-time benefit in the SRTT. In a visual triplet learning paradigm using shape triplets, Bertels et al., (2015b) measured implicit and explicit knowledge through the use of binary knowledge attribution ratings ("guess" and "remember") which were analysed in combination with 2AFC performance for the guessing criterion. Findings were analogous to Weiermann & Meier's (2012), in that no evidence of implicit knowledge was found in children. In fact, those children who acquired sequence knowledge, were found to have conscious access to it.

Daltrozzo & Conway (2014) more recently put forward a developmental model of statistical learning. The authors propose that statistical learning is composed of two systems. The "basic" system, which depends on implicit and automatic mechanisms, is prevalently used from birth until adulthood, when its use declines, and then becomes prevalent again in older adulthood. In contrast, the "expert" system begins to develop in early childhood and is prevalent throughout adulthood. Following this model, it is possible that children primarily make use of implicit knowledge, while adults mostly use explicit knowledge.

In summary, based on the existing literature, we expected both adults and children to acquire knowledge of the statistical regularities in transition matrix stimuli, in both the visual and auditory modalities. With regards to the conscious status of the acquired knowledge, as this is the first piece of research investigating implicit and explicit knowledge in transition matrix stimuli, we were unable to make specific predictions. However, we hypothesised that children would make more use of implicit knowledge than adults.

2.2 Auditory statistical learning in adults

Three versions of the experiment were piloted: first a version using three-element test sequences, then a five-element test sequences version and, finally an eight-element test sequences version. This was to discover the optimal length of test sequences to use in our subsequent experiments.

2.2.1 Participants

Two and four participants were tested for the three-element test sequences and five-element test sequences version of the experiment, respectively. These were undergraduate students at the University of Lincoln who took part in the experiment in exchange for research credit points. Age and gender information was not collected for these participants. Twenty participants took part in the eight-element test sequences version. These were a mixture of undergraduate and postgraduate students at the University of Lincoln, as well as members of the public who took part upon invitation from the experimenter. Gender and age information was missing for six of these participants. Of the remaining 14 participants for whom this information was available, 5 were male (age range = 19 to 57 years, M = 29.80 SD = 16.12) and 9 were female (age range = 24-65 years, M = 43.33 SD = 13.23). All participants had normal or corrected-to-normal vision and no participant had any condition which could have affected their participation in the experiment, or the validity of the data.

2.2.2 Ethics

The study received ethical approval from the University of Lincoln Psychology Research Ethics Committee (see Appendix A for ethical approval form and full details of ethical approval). Participants provided full informed consent and were free to withdraw from the study at any point without providing any motivation, or to withdraw their data at a later point. At the end of the experiment participants were fully debriefed, verbally and in writing (See Appendix B.1 for participant information sheet, consent form and written debrief form).

2.2.3 Three-element test sequences

2.2.3.1 Materials and methods

2.2.3.1.1 Stimuli

Given our emphasis on studying the learning of transition probabilities, we aimed to first test the smallest units which can be learned, which, in a second-order structure, are three-element test sequences. The rationale for this choice was that, if participants had acquired knowledge of transition probabilities, we expected them to be able to distinguish three-element fragments from the exposure stream from unseen three-element fragments.

Our sequences of tone stimuli were generated by using a transition matrix in a similar fashion to Durrant et al., (2011a). A transition matrix contains probabilities for each potential transition between elements based on the previous element(s). Each combination of row and column in the matrix defines the probability that elements associated with that row will be followed by elements associated with that column (Durrant et al., 2011a). Our auditory sequences were constructed from five symbols, implemented as five different pure tones, distinguished by pitch, and had a second-order structure, meaning that it was necessary to be aware of two previous tones to be able to predict the upcoming tone. In fact, when only considering one previous tone, each of the other five tones had equal probability of occurring. Similarly, the tones all occurred an equal number of times, therefore zero-order statistics had no predictive power.

For the purpose of testing the transition matrix method in this experiment, three sets of test sequences were generated: one set of three-element test sequences, one set of five-element test sequences and one set of eight-element sequences. The three-element test sequences version is discussed in this section. The transition matrix (Figure 2.1) consisted of five columns, indexing each possible next tone, and twenty-five rows, indexing all possible combinations of previous two tones. Each row of the matrix contained one high probability (0.9) and four equally low probabilities (0.025), therefore producing sequences of a probabilistic nature, as any two tones were followed by a specific third tone 90% of the time, and by any of the other four tones 2.5% of the time.

		1	2	3	4	5
1	**1**	0.025	0.025	0.025	0.9	0.025
1	**2**	0.025	0.025	0.9	0.025	0.025
1	**3**	0.025	0.9	0.025	0.025	0.025
1	**4**	0.9	0.025	0.025	0.025	0.025
1	**5**	0.025	0.025	0.025	0.025	0.9
2	**1**	0.025	0.025	0.025	0.025	0.9
2	**2**	0.025	0.025	0.025	0.9	0.025
2	**3**	0.025	0.025	0.9	0.025	0.025
2	**4**	0.025	0.9	0.025	0.025	0.025
2	**5**	0.9	0.025	0.025	0.025	0.025
3	**1**	0.025	0.025	0.9	0.025	0.025
3	**2**	0.025	0.9	0.025	0.025	0.025
3	**3**	0.9	0.025	0.025	0.025	0.025
3	**4**	0.025	0.025	0.025	0.025	0.9
3	**5**	0.025	0.025	0.025	0.9	0.025
4	**1**	0.9	0.025	0.025	0.025	0.025
4	**2**	0.025	0.025	0.025	0.025	0.9
4	**3**	0.025	0.025	0.025	0.9	0.025
4	**4**	0.025	0.025	0.9	0.025	0.025
4	**5**	0.025	0.9	0.025	0.025	0.025
5	**1**	0.025	0.9	0.025	0.025	0.025
5	**2**	0.9	0.025	0.025	0.025	0.025
5	**3**	0.025	0.025	0.025	0.025	0.9
5	**4**	0.025	0.025	0.025	0.9	0.025
5	**5**	0.025	0.025	0.9	0.025	0.025

Figure 2.1: Transition matrix used for our three-element and five-element test sequences stimuli, for both the auditory and visual versions. Columns numbered 1-5 (shaded grey) index each possible next element, based on the previous two elements (shaded grey) indicated on each row. Each row/column

combination will give the probability that a particular element (1-5) will occur based on the previous two.

We used five pure tones from the Bohlen-Pierce scale: 261.63Hz, 300.53 Hz, 345.22 Hz, 396.55 Hz and 455.52 Hz, which, in line with Durrant et al. (2011b), was chosen as its intervals are different to those heard in Western tonal music. We could therefore rule out the possibility that the melodic fragments created would be familiar to a Western listener. In order to avoid aliasing edge effects, the tones were Gaussian modulated. The sampling frequency of the tones was 44,100 Hz (CD quality).

A long exposure sound stream, which formed a second-order Markov chain, was generated by sampling the transition matrix. As shown in Figure 2.1, the transition matrix determined the transition probability for the upcoming tone in the sequence based on the previous two tones. The stream had a total duration of four minutes and contained 1091 tones, each lasting 200 msec with a gap of 20 msec in between tones. As the four-minute duration for the exposure stream was achieved by capping an otherwise longer sound stream, the last tone of exposure, that is, the 1091st tone, was interrupted, lasting 180 msec instead of 200 msec.

There were 150 test sequences in total, of which 75 belonged to the structured condition, which was made up of 25 unique structured sequences, each of which was repeated three times. The remaining 75 unique test sequences belonged to the unstructured condition. Test sequences for the structured condition were generated by sampling the same transition matrix which generated the long exposure sequence, and therefore conformed to the same statistical structure as exposure. Test sequences for the unstructured condition were randomly generated, such that each possible upcoming tone in the sequence had the same probability of occurrence. In this version of the experiment, each test sequence contained three tones, therefore only one second order transition, adding up to a duration of 0.66 seconds. This length of test sequences was chosen as we were initially interested in testing knowledge of the smallest units of a sequence, that is, individual transitions. In fact, each three-element test sequence contains one second-order transition. This choice was also based on the successful application of the PDP by a number of motor-learning experiments using the SRTT in which longer second-order conditional sequences were split into "triplets" containing one second-order transition and participants' knowledge of these triplets was tested in the PDP (Fu et al., 2008a) (Fu et al., 2010a) (Fu et al., 2013).

2.2.3.1.2 Apparatus

The experimental stimuli and program were programmed using the Psychtoolbox (Brainard, 1997; Pelli, 1997; Kleiner et al, 2007) in MATLAB R2017a, which was also used for the purpose of running the experiment. The experiment program ran on a Samsung laptop with an Intel ® Core ™ i5 processor and a 15.6- inch screen. Sound stimuli were played in stereo mode through a pair of headphones. All participant responses were collected through the laptop keyboard.

2.2.3.1.3 Procedure

2.2.3.1.4 Exposure phase

Prior to starting the experiment, the participant was asked to wear the headphones and to set the computer volume to a comfortable level for him/ her. The aim of the exposure, or learning, phase was to familiarise participants with the transition probabilities in the exposure stream. Participants were instructed to listen attentively, but no mention was made of the statistical regularities in the exposure stream, or that the exposure phase would be followed by a test phase. The following instructions appeared on the screen: "You will hear a series of tones. Please listen attentively. Press a key to hear the tones." Overall, the exposure phase lasted approximately five minutes.

2.2.3.1.5 Test phase

The exposure phase was immediately followed by a test phase containing 75 two-alternative forced-choice (2AFC) trials. Each trial consisted of two test sequences, one structured, sharing the same statistical structure as the exposure stream, and one unstructured sequence, which the participant had not heard before. There were 25 unique structured sequences, each of which appeared three times during the test (giving 75 structured sequences in total throughout the test phase) and 75 unique unstructured sequences. The order of presentation of the 75 structured test sequences was randomised per participant such that all 25 unique structured sequences were presented first, and then a second and third time. The order of presentation of the 75 unstructured sequences was also randomised per participant.

The two test sequences were presented sequentially. The labels “sequence 1” and “sequence 2” appeared in the centre of the computer screen for the duration of 500 msec before the first and second sequence respectively. These labels were displayed in black writing against a white background. No visual stimulus was on screen whilst the tone sequences were playing, although the full-screen white background displayed through the Matlab Psychtoolbox on-screen window was only closed at the end of the experiment. There was a 500-msec pause between the end of sequence one and presentation of the “sequence 2” label. In half of the 50 forced-choice trials the structured test sequence was presented first and in the other half the unstructured test sequence was presented first. The order of presentation of the structured and unstructured test sequences within each trial was randomised. Each trial was separated by the next trial by a one-second pause.

In order to assess the conscious status of knowledge with the PDP, the 2AFC task was administered twice: once under inclusion instructions and once under exclusion instructions. The two sets of instructions contained the same structured and unstructured sequences each time, therefore the instructions were all that changed between the conditions. On-screen instructions were given at the beginning of each of these two test phases. These stated: “Choose which of two sequences is CORRECT. Press Enter to play the sequences”, for inclusion instructions and “Choose which of two sequences is INCORRECT. Press Enter to play the sequences” for exclusion instructions.

A response was required after both the structured and unstructured sequences had been presented. Responses were made by pressing the “1” or “2” number keys in the upper left corner of the computer keyboard. Participants pressed “1” to choose the first sequence that was presented in the 2AFC trial and "2" to choose the second sequence that was presented. On-screen instructions were used on each trial after both the structured and unstructured sequences had been played to prompt the participant to respond and to remind them of the response keys. These appeared on the screen on three separate lines, to ensure clarity: "Respond now", "1 = sequence 1", "2 = sequence 2".

For the purpose of the guessing and zero correlation criteria, confidence and knowledge attribution ratings were collected after each 2AFC trial. For consistency with previous studies (Zoltán Dienes, 2007) confidence ratings were measured on a continuous scale from 50 to 100. During the verbal instructions at the beginning of the test phase, participants were advised that 50 was a guess (the experimenter advised "you may as well have flipped a coin"), and 100 was complete certainty in their response (Zoltán Dienes, 2007). After participants had made their 2AFC choice, the following instructions appeared on screen: "How confident are you in your choice? Type in a number 50-100". Participants used the number keys on the keyboard to make their response. After this, knowledge attribution ratings were collected. On screen instructions asked participants: "What is the basis of your judgement?". Underneath these instructions, the response keys were detailed: 1 for guess, 2 for intuition, 3 for rules and 4 for memory. The "rules" attribution, used in Artificial Grammar Learning, is a structural knowledge attribution (Andy D. Mealor & Dienes, 2013). We aimed to test its use with transition matrix to assess our participants' depth of knowledge of transition probabilities. Participants pressed a key 1-4 to indicate their choice. After both confidence and knowledge attribution ratings were collected, a new 2AFC trial was presented. The task was self-paced, with no response timeout for any of the responses required.

After participants had completed the 75 2AFC trials for inclusion, the exclusion test was administered. To counteract any order effects of administration of inclusion and exclusion tasks, half the participants were administered inclusion first and the other half was administered exclusion first. Before the beginning of the test phase, both before inclusion and exclusion, participants also received standardised verbal instructions to prepare them for what to expect in the upcoming phase and to explain the meaning of the different knowledge attribution ratings. For the standardised verbal instructions refer to Appendix C. Overall, the test phase lasted approximately 30 minutes.

2.2.3.2 Results

This was a pilot experiment which aimed to establish, first, whether participants' knowledge of the auditory sequence structure allowed them to perform above-chance in our forced-choice tasks, and, secondly, whether the PDP and guessing/ zero correlation criteria can be applied to measure implicit and implicit knowledge in this paradigm. The proportion of correct responses for our participants in this version of the experiment (3-element test sequences) was 0.48 for one participant and 0.4 for the other participant. We calculated the proportion of correct responses required to perform individually above chance in our 2AFC task to be 0.6[3], therefore none of our two participants performed above individual chance. We considered this an indication that the three-element test sequences task was too difficult for participants to express their knowledge of the sequence structure, therefore we did not carry out any further data collection or analysis for this group. Furthermore, in order to assess statistical power, GPower (Faul & Erdfelder, 1992), version 3.1.9.2, was used to calculate the required sample size for a one-sample t-test to detect a medium-size effect at an alpha rate of 0.05, one-tailed, with power ($1 - \beta$) set at 0.95. A one-sample t-test would have been used in our analysis to assess whether participants' performance in the task significantly differed from chance level (0.5 in the case of our forced-choice task). Based on a required N of 45 to obtain

[3] The threshold for individual above-chance performance was calculated using the binomial distribution to obtain information on the probability of obtaining any one outcome and, through use of the cumulative distribution function, the probability of obtaining any outcome below or above a certain number of trials. Therefore, in order to compute, in MATLAB, the minimum number of correct trials required to be above chance for a one-tailed outcome, we used the following formula: *N = 75; c = 2; L2 = binoinv(0.95,N,1/c)*, where N is the number of trials, 75 in the case of the present 2AFC task, c is the number of choices per trials, based on only one correct choice in our 2AFC task, L2 is a vector containing the limit for above chance performance. A 5% alpha rate was used.

sufficient statistical power, we cannot rule out that a learning effect may have been observed if we had tested a larger number of participants.

2.2.4 Five-element test sequences

2.2.4.1 Materials and methods

2.2.4.1.1 Stimuli

The auditory stimuli for this version of the experiment were identical to the three-element test sequences version, and using the same transition matrix, with the only difference being the length of test sequences, five tones instead of three, adding up to a duration of 1.1 seconds per sequence. Each five-element test sequence contained three second-order transitions.

2.2.4.1.2 Procedure

The procedure for this version of the experiment was identical to the three-element test sequences version. The only difference was the length of the test sequences.

2.2.4.2 Results

The average proportion of correct responses for our group of four participants in this experiment version was 0.52 (*SD* = 0.08). Only one of the four participants performed individually above chance, based on the minimum proportion of correct responses required to perform individually above chance, 0.6. Similar to the three-element version, thislevel of performance was deemed too poor to proceed with this task , and we therefore stopped data collection and analysis for this group. Based on the same power analyses which we carried out for the three-element test sequences version of the task, an N of 45 would be required to obtain sufficient statistical power in a one-sample t-test. We therefore cannot rule out that a learning effect may have been observed if we had tested a larger number of participants.

2.2.5 Eight-element test sequences

2.2.5.1 Materials and methods

2.2.5.1.1 Stimuli

The eight-element test sequences version of the experiment followed the same principles of the previous two versions but used a deterministic transition matrix instead, in order to ensure maximal learning by the participants (Figure 2.2). For each combination of two tones within the sequence there was only one possible subsequent tone, with 100% probability of occurring, therefore not allowing for uncertainty or noise. Exposure consisted of one, long, deterministic sequence with the same parameters as the exposure stream in the three-element and five-element test versions. The test sequences consisted of eight tones, adding up to a duration of 1.76 seconds per sequence. In the same way as for the other experiment versions, the structured test sequences were obtained by sampling the deterministic transition matrix and the unstructured test sequences were randomly generated. In order to shorten the duration of the experiment, the total number of test sequences was reduced from 150 to 100, with 50 structured sequences in total (made up of two repetitions of each of 25 unique structured sequences) and 50 unique unstructured sequences

		1	**2**	**3**	**4**	**5**
1	**1**	0	0	0	1	0
1	**2**	0	0	1	0	0
1	**3**	1	0	0	0	0
1	**4**	0	1	0	0	0
1	**5**	0	0	0	0	1
2	**1**	0	0	1	0	0

2	**2**	1	0	0	0	0
2	**3**	0	1	0	0	0
2	**4**	0	0	0	0	1
2	**5**	0	0	0	1	0
3	**1**	1	0	0	0	0
3	**2**	0	1	0	0	0
3	**3**	0	0	0	0	1
3	**4**	0	0	0	1	0
3	**5**	0	0	1	0	0
4	**1**	0	0	0	0	1
4	**2**	0	0	0	1	0
4	**3**	0	0	1	0	0
4	**4**	1	0	0	0	0
4	**5**	0	1	0	0	0
5	**1**	0	1	0	0	0
5	**2**	0	0	0	0	1
5	**3**	0	0	0	1	0
5	**4**	0	0	1	0	0
5	**5**	1	0	0	0	0

Figure 2.2: Deterministic transition matrix used for our eight-element test sequences stimuli for both the auditory and visual versions. Columns numbered 1-5 (shaded grey) index each possible next element, based on the previous two elements (shaded grey) indicated on each row. Each row/column combination will give the probability that a particular element (1-5) will occur based on the previous two.

2.2.5.1.2 Procedure

The procedure for this version of the experiment was identical to the three-element test sequences version. The only difference was the length of the test sequences.

2.2.5.2 Results

Given the higher levels of performance attained by participants in the eight-element test sequences version of the experiment, compared to the other test versions, we continued data collection in this group to reach a sample size of 20 participants. The average proportion of correct responses obtained in this group was 0.66 (*SD* = 0.10). We therefore proceeded with the analysis of implicit and explicit knowledge through the application of the PDP and the guessing/ zero correlation criteria.

Process Dissociation Procedure

The proportion of structured (training) sequences chosen in the 2AFC task was our dependent variable for the PDP. This was compared to chance level (0.5 in a 2AFC task) separately for the inclusion and exclusion conditions. The proportion of structured sequences was also compared between the two sets of instructions. The PDP results suggested that knowledge was explicit in our participants. The proportion of structured sequences chosen (M = 0.66, SD = 0.11) was significantly above chance (0.5) under inclusion conditions, $t(19) = 6.826$, $p < .001$, one-tailed, 95% CIs [0.095 0.226], Cohen's d = 1.526, and significantly below chance under exclusion conditions, with an average proportion of structured sequences chosen of 0.35 (SD = 0.11), $t(25) = -6.210$, $p < .001$, two-tailed, 95% CIs [-0.216 -0.083], Cohen's d = - 1.389. Reinforcing these results, a paired-samples t-test showed that the proportion of structured sequences chosen was significantly higher under inclusion than exclusion conditions, $t(19) = 6.784$, $p < .001$, two-tailed, 95% CIs of the difference [0.214 0.404], Cohen's d = 1.517. For an illustration of the PDP see Figure 2.3.

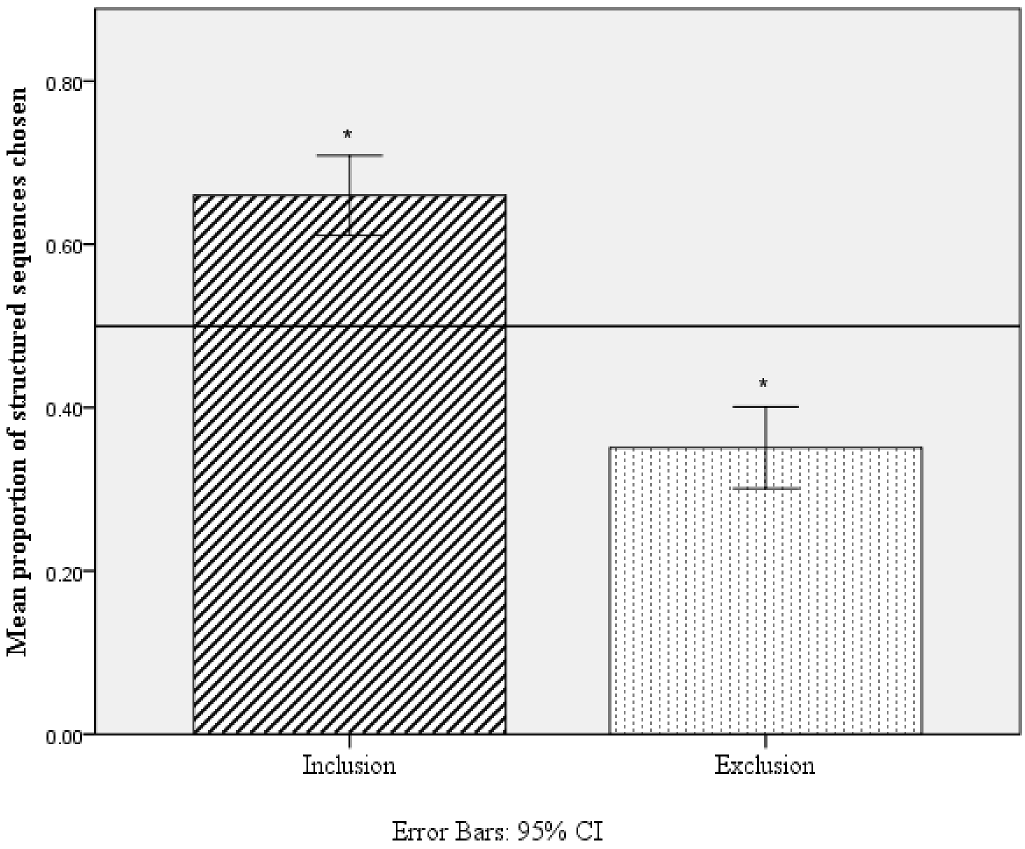

Figure 2.3: Mean proportion of structured (training) sequences chosen under inclusion and exclusion conditions (PDP). Line represents chance level (0.5). Conditions in which performance significantly differed from chance are marked with an asterisk (*).

Guessing and zero correlation criteria

For the purpose of the guessing criterion, the proportion of correct responses in trials in which participants claimed that they were using each of the four knowledge attribution types was compared to chance level. To the best of our knowledge, we do not know of any study which has applied the guessing criterion to the exclusion condition of the PDP. As we believe this could shed light on both implicit and explicit processes, and on how our measures of conscious knowledge operate, we also applied this criterion to the exclusion condition. Explicit knowledge emerged: as can be seen in Table 2.1, under inclusion, performance was at chance when participants claimed that they were guessing and above chance for all other knowledge attributions. Under exclusion, performance was significantly below chance when guessing, which indicates a very low proportion of correct responses when using this knowledge attribution, further supporting our finding that knowledge was explicit, and significantly above chance for all other types of knowledge attributions. For a representation of the guessing criterion refer to Figures 2.4 and 2.5.

		N	**Mean (SD)**	***t***	**df**	***p***	**Cohen's *d***
Inclusion	**Rules**	16	0.64 (0.32)	1.776	15	.048*	0.444
	Memory	18	0.71 (0.17)	5.205	17	>.001**	1.227
	Intuition	19	0.58 (0.15)	2.455	18	.013*	0.563
	Guess	18	0.54 (0.26)	.718	17	.242	0.169
Exclusion	**Rules**	14	0.81 (0.19)	6.148	13	>.001**	1.643
	Memory	16	0.68 (0.26)	2.792	15	.014*	0.698
	Intuition	19	0.63 (0.16)	3.599	18	.002*	0.826
	Guess	17	0.39 (0.20)	-2.382	16	.030*	-0.578

Table 2.1: One-sample t-tests comparing the proportion of correct responses for each of the three knowledge attributions to chance level (0.5) – guessing criterion. Results are displayed separately for inclusion and exclusion conditions and for condition of speed. Significant p-values are marked with one asterisk (*) for significance at the 0.05 level and two asterisks (**) for significance at the 0.01 level. Results for inclusion are one-tailed

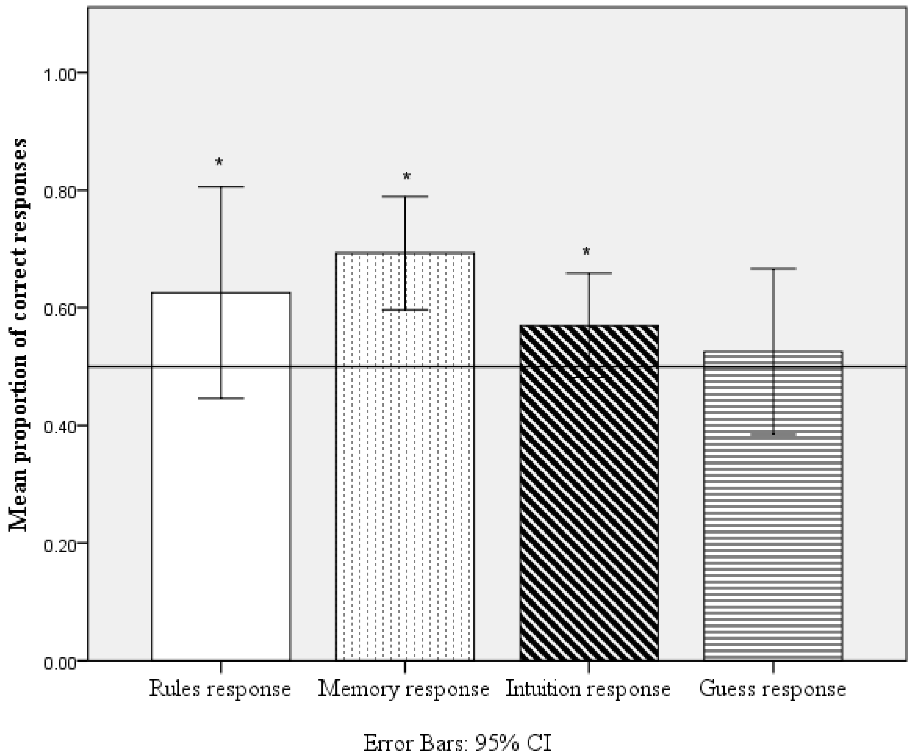

Figure 2.4: Mean proportion of correct responses in the 2AFC task separately for each type of knowledge attribution (guessing criterion) under inclusion instructions. Line represents chance level (0.5). Conditions in which performance was significantly different from chance are marked with one asterisk (*).

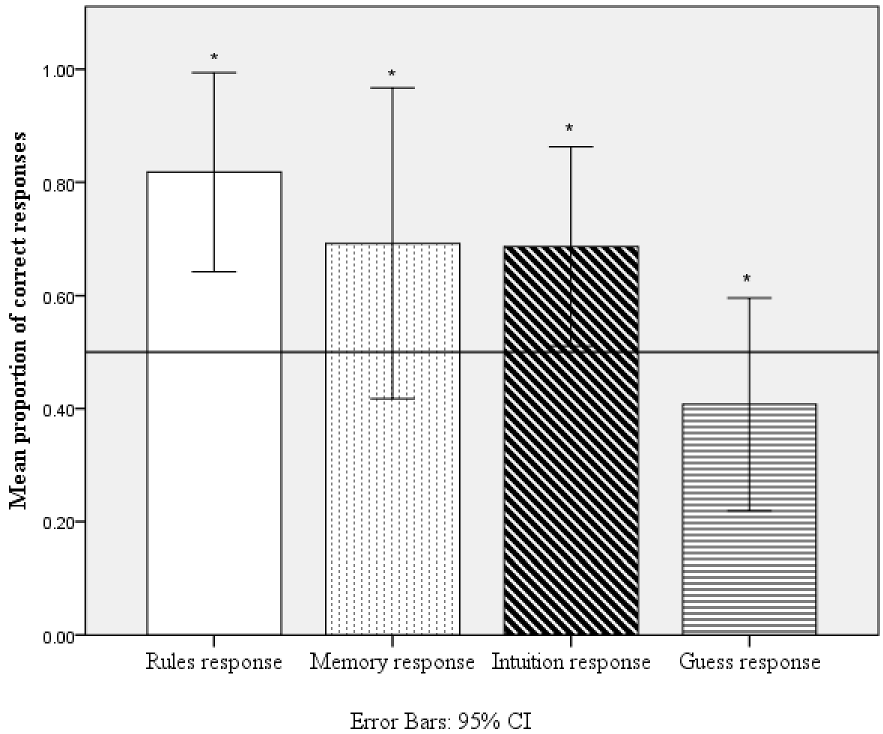

Figure 2.5: Mean proportion of correct responses in the 2AFC task separately for each type of knowledge attribution (guessing criterion) under exclusion instructions. Line represents chance level (0.5). Conditions in which performance was significantly different from chance are marked with one asterisk (*).

These results were confirmed by the zero correlation criterion, indicating that, under both inclusion and exclusion, confidence ratings were significantly higher in trials in which participants were correct than in trials in which they were wrong (Table 2.2).

PDP condition	**Response correctness**	***N***	**Mean (SD)**	***t***	**df**	***p***	**Cohen's *d***	**95% Cis of the difference**
Inclusion	Correct	20	78.82 (8.90)	4.362	19	>.001**	0.975	[3.206 9.121]
	Incorrect	20	67.65 (7.49)					
Exclusion	Correct	20	73.91 (10.28)	4.332	19	>.001**	0.969	[3.532 10.167]
	Incorrect	20	67.06 (8.03)					

Table 2.2: Results of paired-samples t-tests comparing confidence in trials when participants were correct and when they were incorrect (guessing criterion). Results are displayed separately for inclusion and exclusion conditions. Significant p-values are marked with one asterisk (*) for significance at the 0.05 level and two asterisks (**) for significance at the 0.01 level.

2.2.6 Discussion

The present experiment replicated findings of previous transition matrix work (Durrant et al., 2011b; Durrant et al., 2013b) that adult participants, after familiarisation with a long tone sequence, are able to distinguish tone sequences which share the same statistical structure as the familiarisation stream from unstructured tone sequences. This finding of successful learning was expected, given that learning in previous work (Durrant et al., 2011b; Durrant et al., 2013b) was observed when using sequences with a probabilistic structure. Due to the higher level of noise, we expected that learning of the statistical structure of probabilistic stimuli would have been more challenging for participants.

In a statistical learning paradigm, participants learn to segment word-like units solely on the basis of transition probabilities between individual elements (Saffran et al., 1996). We reasoned that, if individual second-order transitions between two given tones and the subsequent tone had been learned, participants would have performed above chance in the 2AFC task. This hypothesis was further reinforced by findings of SRTT studies in which participants, based on a two-movement cue, were able to reproduce the third movement of "triplets" belonging to the second-order conditional sequences responded to during training (Fu et al., 2013). In the present experiment, participants were not able to express their knowledge of the exposure sequence when tested with three-element test sequences, which contained one second-order transition, or five-element test sequences, which contained three second-order transitions. This suggests that in existing studies (Fu et al., 2013), given that participants have to respond via keypresses to the first two, cued, movements, their muscle memory of the training sequence greatly helps in the generation of the third movement of a "triplet". Therefore, despite the two tasks are based on the same type of statistics, we cannot make meaningful comparisons between the present study and previous SRTT work.

Using an auditory triplet learning paradigm, Saffran et al., (1999) showed that participants are able to segment three-element tone words from a continuous tones stream on the basis of transition probabilities. However, their experiment relied on a concatenation of only six auditory triplets, each of which was presented 18 times during their exposure. In contrast, our transition matrix in the present experiment contained twenty-five possible second-order transitions, therefore presenting a much greater challenge for participants. In their transition matrix studies, Durrant et al., (2013b, 2011b) used test sequences which were 18-element long, therefore containing 16 second-order transitions. The present experiment showed that, when participants are given enough information within the test sequences, specifically, a minimum of six transitions, they are able to successfully relate the test sequence to the exposure sequence for the purpose of the forced-choice task.

Based on these findings, we suggest that successful performance in this task relies on participants relating longer tone patterns within the test sequences to what they heard during exposure, rather than segmenting independent units within the exposure stream. We extend this suggestion by proposing that participants may have relied on general properties of the test sequences to make their discriminations in the forced-choice task. For example, how many same-tone repetitions were present and the pitch of any repeated tones. A sequence preference analysis would have been informative in this respect, to see if, for example, those test sequences which contained a higher number of repetitions were also the ones that participants classified more correctly. However, as our test phase in this experiment only contained two instances of each individual test sequences, the power of this analysis would have been too low for meaningful interpretation.

This is the first experiment which has used the PDP to assess implicit and explicit knowledge with tone stimuli in the context of a forced-choice task. To the best of our knowledge, we are only aware of one other study in Sequential Regularities Learning which has used the PDP with auditory stimuli (Franco et al., 2011a), but these consisted of artificial speech sequences and the PDP was implemented using a yes/ no task, rather than a forced choice between two test sequences. The authors found that participants had conscious control of the knowledge they had acquired, which is in line with our findings in this experiment.

When giving further consideration to our specific application of the PDP as a forced-choice task, it could be argued that, in our task, participants were responding under inclusion in the opposite way to their previous response under exclusion, and vice-versa, and that this may be sufficient for participants to perform well in the task, which is therefore not a genuine measure of implicit and explicit knowledge but, rather, the reflection of participant performance strategies. Although we recognise that a generation task requires participants to access their memory of the studied material, therefore more directly tapping into the stimulus material that is being studied, we suggest that it runs the risk of biasing participants towards explicit knowledge, as it requires the use of explicit recollection. In contrast, we suggest that a 2AFC task is more suitable to access implicit knowledge, in that it does not require participants to explicitly recollect what they have learned, as both response options are presented on each trial.

It must also be considered that the application of the PDP with a generation task to our statistical learning stimuli in this Thesis, particularly the auditory stimuli, poses considerable methodological challenges. Our implementation of the PDP with a 2AFC task has made these investigations possible. Furthermore, in order to mitigate the effects of the possible use of performance strategies in the PDP, we have taken care to randomise the order of administration of the inclusion and exclusion conditions. Given our successful application of the PDP, we decided to retain this method for future investigations in the auditory modality.

Overall, based on these results, we concluded that, in a transition matrix paradigm, for the knowledge acquired to be expressed in a forced-choice task, test sequences must have a minimum length of eight elements. Therefore, we decided to retain this length of test sequences in our future investigations using transition matrix. With regards to the status of knowledge, the PDP and guessing/ zero correlation criteria converged in indicating that, when knowledge was demonstrated in the 2AFC task, this was held entirely explicitly by our participants. This is a novel finding, as no research has been carried out to date investigating the status of knowledge acquired in the learning of auditory sequences generated through transition matrix. Previous research (Durrant et al., 2011b; Durrant et al., 2013b) has conceptualised this as an implicit learning paradigm. Our findings added to this research by indicating that the knowledge that participants develop about the training stimuli is explicit.

2.3 Auditory statistical learning in children

2.3.1 Materials and methods

2.3.1.1 Participants

Participants were recruited through the University of Lincoln Summer Scientist event, held annually by the School of Psychology, in which children aged 3 to 10 years and their parents take part in a variety of research studies run by academic staff at the university. In total, 44 participants took part in the experiment: thirteen participants were 10 years old (3 males and 10 females), twenty-two participants were 9 years old (13 males and 9 females), eight participants were 8 years old (3 males and 5 females) and one participant was 7 years old (male). The overall mean age for our sample was 9.09 years (*SD* = 0.71). One participant had a diagnosis of dyslexia and one had a diagnosis of autism.

2.3.1.2 Ethics

The study received ethical approval from the School of Psychology Research Ethics Committee (SOPREC) as part of the University of Lincoln Summer Scientist Week, and parental consent was obtained centrally as part of this (see Appendix B.2.1 for ethics application as part of Summer Scientist Week). The researcher provided parents with additional information regarding the experiment, named "Musical Notes" as part of Summer Scientist Week, which contained a written debrief (see Appendix B.2.2 for additional information for parents). Before taking part in the experiment, each individual participant also provided verbal consent, indicating that they wished to play the "Musical notes" game. Participants were free to withdraw from the study at any point without providing any motivation. At the end of the game, the experimenter explained the purpose of the game.

2.3.1.3 Stimuli

The auditory stimuli for this experiment were the same as those for the experiment on adults, using eight-element deterministic sequences. The stimuli were generated from the same deterministic transition matrix.

2.3.1.4 Apparatus

The apparatus used for this experiment was identical to that of our auditory transition matrix experiment on adults.

2.3.1.5 Procedure

2.3.1.5.1 Exposure phase

In order to maintain the children's attention to the exposure stream, we used a cover task during this experiment phase, which involved participants making a speeded key press to distractor tones embedded in the exposure stream. The exposure stream which we used in our experiment on adults was modified for this purpose. Distractor tones were of the same pitch as the five tones which made up our auditory stimuli, but had a different timbre, therefore sounded as if they were played by a different musical instrument to the regular tones. No new tones were added to the exposure stream for the purpose of this task but, rather, tones at different random points within the exposure stream were altered in pitch, therefore becoming distractor tones. This was to avoid disrupting the statistical structure of the exposure stream. The placement of distractor tones within the exposure stream was different for each participant. The average gap between distractors was 5 seconds with a 1-second maximum variation either side of this mean. Of the total 1091 exposure tones, 48 were distractor tones, therefore nearly 5% of tones in the exposure stream were distractors. Each tone lasted 200 msec, except for the last tone, which lasted 180 msec, and there was a 20 msec gap between tones. The distractor tones had the same duration as the regular tones.

Participant instructions were analogous to those for adults, in that no mention was made of the presence of statistical regularities in the exposure stream, but they were adapted to be more child-friendly. Children were alerted that they would hear different-sounding notes at various points during exposure, and were instructed to respond to these by pressing the space bar on the computer keyboard as quickly as possible upon hearing them (see Appendix B.2.3 for full task instructions). A practice tone stream containing the same tone classes as the real exposure stream, but in random order, was played as a demonstration to ensure that participants understood the difference between regular tones and distractor tones. The practice stream lasted 15 seconds and the distractor tones were more frequent, with an average of three seconds between them. Before starting the task, participants were asked to wear the headphones, and the volume was set to a comfortable level for them.

2.3.1.5.2 Test phase

We did not use the PDP as a measure of conscious knowledge in this experiment, therefore we administered the 2AFC task under inclusion conditions only. This is because of the complexity of exclusion instructions, which we deemed to be too high for children. Using the PDP would have also lengthened the task beyond what was deemed acceptable for children's concentration levels. The 2AFC task was identical to the inclusion condition in our experiment on adults, with the exception that the conscious status of knowledge was assessed through binary knowledge attributions: "guess" and "remember". This choice was made on the basis of previous statistical learning experiments which have applied the guessing criterion with children (Bertels et al., 2015a). We took guess knowledge attributions in correct trials to indicate implicit knowledge, and remember attributions in correct trials to indicate explicit knowledge. Knowledge attributions were collected after each forced-choice trial. Responses were recorded in a similar way as for the adult version of the experiment: choice of sequence 1 or sequence 2 was recorded through letters "q" and "p" on the keyboard, respectively, and choice of a guess or remember attribution was recorded through the number keys "1" or "2" on the keyboard, respectively. In order to prevent errors due to accidental key-presses, participants told their responses to the experimenter, who recorded these through the keyboard.

2.3.1.6 Additional measures: questionnaire for parents

A short questionnaire was administered to the parents of our participants. This was to assess the children's performance in, and enjoyment of, mathematics, English, science, foreign languages and art, as well as their musical sophistication. Based on suggestions by previous correlational studies (Siegelman, Bogaerts, Christiansen, & Frost, 2017) that language, mathematical abilities, and musical abilities might correlate with statistical learning, we were interested in explaining some of the individual variability in our participants' performance. Academic performance and enjoyment of the different school subjects were both assessed on a 10-point Likert scale, where higher scores indicated higher performance/ enjoyment. The participants' level of musical training was assessed using the musical training subscale of the Gold-MSI questionnaire (Müllensiefen, Gingras, Musil, & Stewart, 2014), a widely used measure of musical sophistication. See Appendix B.2.4 for questionnaire for parents.

2.3.2 Results

2AFC performance

The proportion of training sequences chosen in the 2AFC task (M = 0.61 SD = 0.11) was significantly above chance (0.5), $t(43) = 6.760$, $p < .001$, one-tailed, 95% CIs [0.058 0.163], Cohen’s *d* = 1.019, indicating that our participants had acquired knowledge of the statistical structure of the stimuli.

In order to assess whether there were any differences in performance between our three age groups, we carried out a one-way between-subjects ANOVA with age as a factor and performance in the 2AFC task as the dependent variable. Given that only one participant was 7 years old, data for this participant was pooled with data for the 8-year-olds for the purpose of this analysis. The ANOVA did not show any age-related differences in performance, $F(2, 41) = 1.713$, $p = .193$, $\eta^2_p = 0.077$.

Guessing and zero correlation criteria

Overall, our participants used significantly more remember ($M = 0.63$ $SD = 0.17$) than guess ($M = 0.37$ $SD = 0.17$) attributions in this task, $t(43) = -5.012$, $p < .001$, two-tailed, 95% CIs of the difference [-0.356 -0.152], Cohen’s $d = 0.756$, which points to high confidence and explicitness of knowledge.

The proportion of correct responses in trials in which participants were guessing ($M = 0.55$, $SD = 0.17$) was significantly above chance, $t(43) = 2.144$, $p = .019$, one-tailed, 95% CIs [-0.013 0.122], Cohen’s $d = 0.323$. When participants were using memory, the proportion of correct responses was higher than for guessing ($M = 0.65$ $SD = 0.12$) and also above chance, $t(43) = 8.039$, $p < .001$, one-tailed, 95% CIs [0.094 0.206], Cohen’s $d = 1.212$ (Figure 2.6). Based on the guessing criterion, these results indicated that both implicit and explicit knowledge were present. In order to compare the relative levels of implicit and explicit knowledge, we ran a paired-samples t-test between the proportion of correct responses when participants were guessing and when they were using their memory. We found this difference to be significant, $t(43) = 3.536$, $p = .001$, two-tailed, 95% CIs of the difference [0.041 0.151], Cohen’s $d = 0.533$, with a higher proportion of correct responses when remembering than when guessing, and took this to show that explicit knowledge was more prominent in our participants.

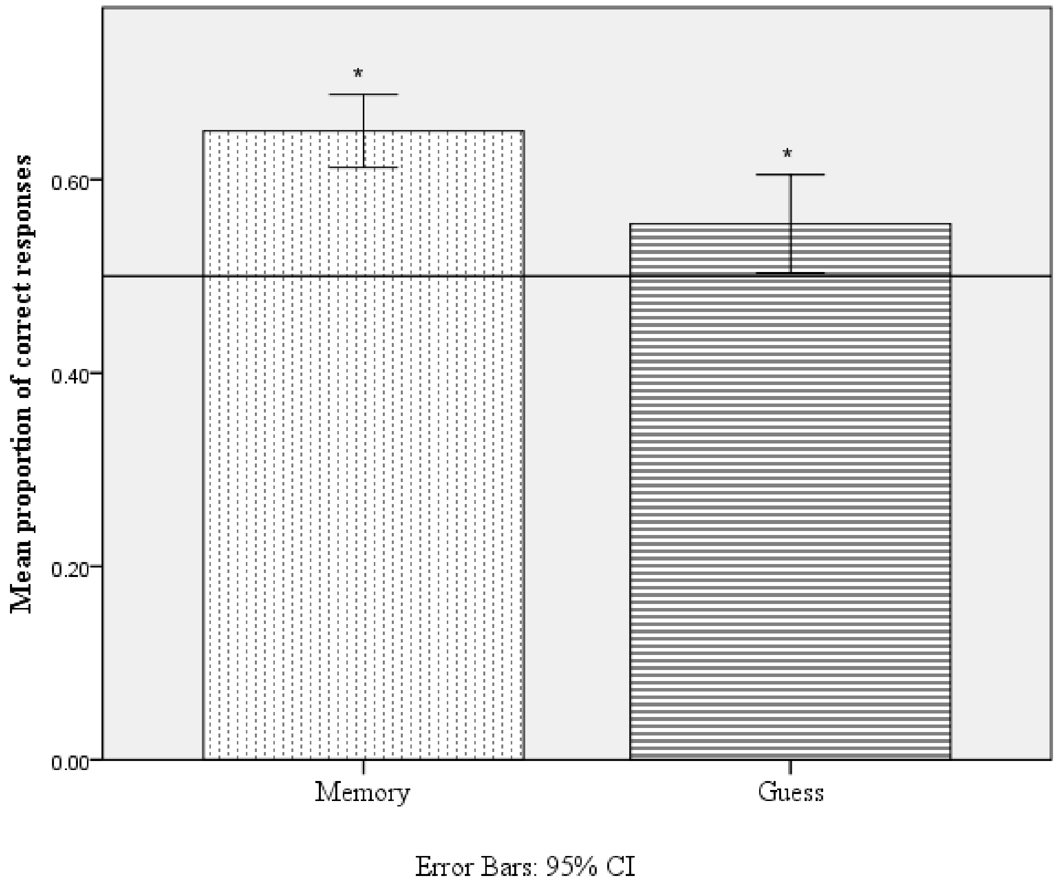

Figure 2.6: Mean proportion of correct responses separately for memory and guess attributions (guessing criterion). Line represents chance level (0.5). Conditions in which performance was significantly above chance are marked with one asterisk (*).

Correlational analyses

Our correlational analyses found a significant relationship between the proportion of correct responses in the 2AFC task and parents' ratings of their children's performance in mathematics ($N = 41$, $r = .334$, $p = .033$) English ($N = 41$, $r = .479$, $p = .002$) and science ($N = 41$, $r = 410$, $p = .008$), and also of their enjoyment of English ($N = 40$, $r = .366$, $p = .020$). Interestingly, there was no correlation between 2AFC performance and musical training, but we found a significant negative correlation between the proportion of guess responses and musical training (Figure 2.7), indicating that participants who were more musically trained felt that they relied less on guessing in the task.

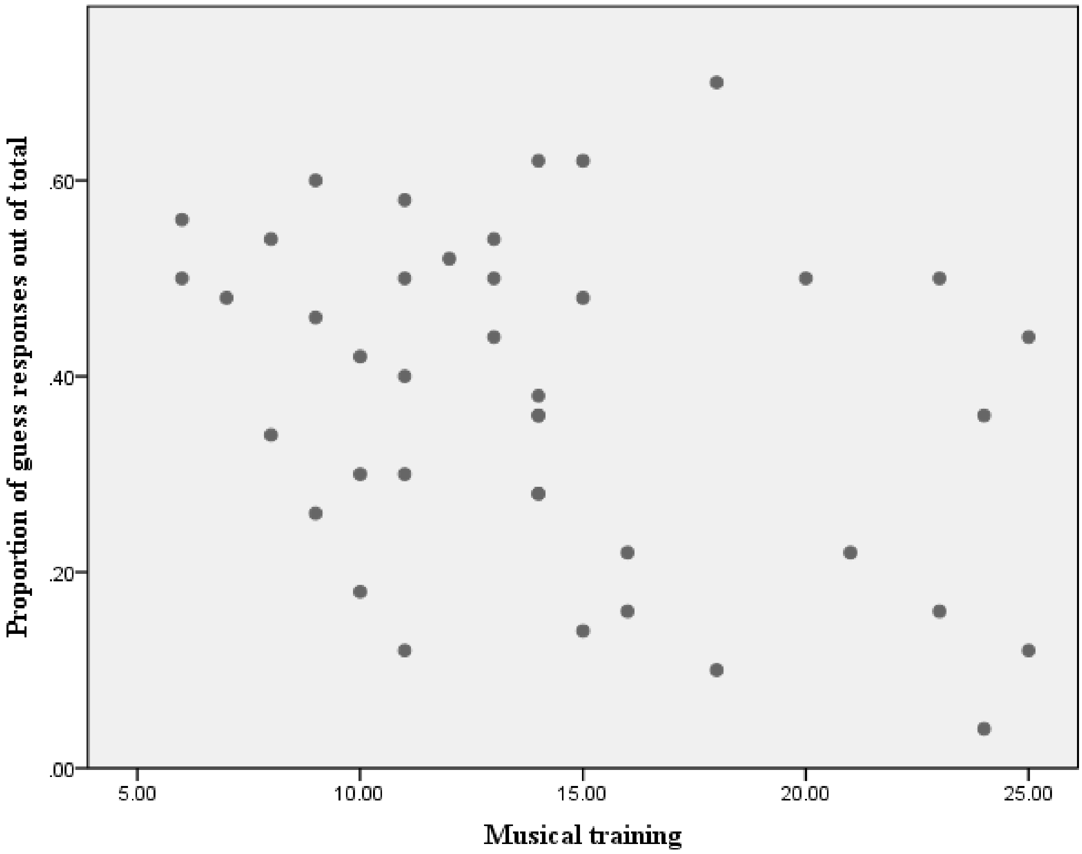

Figure 2.7: Scatterplot representing the relationship between the proportion of guess responses and the musical training subscale of the Gold-MSI questionnaire.

2.3.3 Discussion

The present experiment found that children are able to learn the statistical structure of tone stimuli generated using a transition matrix, and can apply this knowledge in a forced-choice recognition task by correctly distinguishing between test sequences which belong to the exposure stream and unstructured test sequences. This is a novel finding in the Sequential Regularities Learning field, as, to date, no studies have used a transition matrix paradigm with children.

Regarding the status of the acquired knowledge, the guessing criterion appeared to suggest that some implicit knowledge was present, as the children's performance was above chance in trials in which they claimed that they were guessing. However, the results of our comparison between correct responses when remembering and when guessing seemed to indicate that explicit knowledge was more prominent than implicit knowledge in our participants, counter to previous proposals (Koriat & Ackerman, 2010), that children of this age are not able to track their knowledge.

We took our data to mean that the children in the present experiment held their knowledge of the sequences mostly explicitly, an interpretation reinforced by the fact that significantly more remember than guess attributions were used in the task overall. This prevalence of explicit knowledge is backed up by research in the domain of visual statistical learning, which also indicates that children acquire explicit knowledge (Weiermann & Meier, 2012; Bertels et al., 2015b). Given that our experiment on adults showed entirely explicit knowledge in that group, and that we found mostly explicit knowledge in children, we could not confidently support Daltrozzo & Conway's proposal (2014) that implicit knowledge is more prevalent in children. Based on our finding that children's performance was above chance when they claimed to be guessing, however, we suggest that future research should explore the authors' proposal further, as the present evidence is not conclusive in this respect.

We found no differences in performance between our three age groups in this experiment, a finding which goes against proposals that performance in Sequential Regularities Learning improves with age (Vaidya et al., 2007; Arciuli & Simpson, 2012b; Arciuli & Simpson, 2011), at least in the three age groups that we have used in this experiment. It would be interesting in future research to include both younger and older groups of children, to determine at which point in their development they become able to discriminate between structured and unstructured sequences. In terms of comparing performance between our two age groups, the learning effect in adults was only very slightly higher than in children, indicating that the two groups have learned auditory statistical regularities with the same efficiency. However, it is possible that, if we had carried out a systematic comparison of a larger number of age groups, we would have observed a developmental effect in children's statistical learning.

When comparing results of the guessing criterion between the adults and children groups, it is important to bear in mind the difference in the types of knowledge attribution ratings that were used. In fact, based on previous research which has used the guessing criterion with children (Bertels et al., 2015a), we expected the "intuition" attribution, as well as any other attributions such as "rules", to be too complex to understand for children between the ages of 8 and 10. This was contradicted by occasional verbal reports by our participants, regarding certain discriminations in the forced-choice task, that their knowledge was "neither of those" or "somewhere in between". This is an important indication that children within the age range that we tested may, indeed, be able to make use of "intuition" attributions, and we suggest that future similar research should introduce intuition attributions for use with these age groups.

Finally, we found a significant correlation between the proportion of correct responses in the 2AFC task and parents' ratings of their children's performance in mathematics, English and science, and also of their enjoyment of English. This is an interesting finding, which is not only in line with research suggesting that statistical learning in children is related to language abilities, such as understanding of syntax (Kidd, 2012) and reading (Treiman, 2018), but also suggests that statistical learning is related to general academic performance and attainment in school. We also found that participants who had a higher level of musical training had more confidence in their performance in the task, shown by their feelings of less reliance on guessing.

Interestingly, this finding was not accompanied by a significant correlation between musical training and forced-choice task performance, as would be expected on the basis of recent findings that musicians are better statistical learners than non-musicians (Mandikal Vasuki et al., 2017). Instead, we found that musical training only had an effect on our participants' subjective assessment of the type of knowledge that they were using.

Overall, this experiments added to the existing literature by discovering that statistical learning of auditory regularities, tested through a transition matrix paradigm, occurs in children. Based on the evidence we gathered, it could be concluded that the quality and nature of this knowledge in children is not different to adults, and that it is explicit in both age groups. We cannot exclude, however, that future research testing a wider age range of children may observe a developmental effect of explicit knowledge in children. The extent of implicit knowledge of auditory regularities in children, however, will need to be clarified further in future research.

2.4 Visual statistical learning: piloting the transition matrix paradigm

In the same way as for the auditory experiment, three versions of the task were trialled in turn, using three-element, five-element and eight-element test sequences, in order to establish the most suitable test for the study of visual statistical learning.

2.4.1 Participants

Two participants were tested for the three-element test sequences version of the experiment, one participant for the five-element test sequences version and two participants for the eight-element test sequences version. Participants were undergraduate students at the University of Lincoln who took part in the experiment in exchange for research credit points. Age and gender information was not collected. There were no age restrictions for taking part. All participants had normal or corrected-to-normal vision, and no participant had any medical condition which could have affected their participation or the validity of the data.

2.4.2 Ethics

The study received ethical approval from the University of Lincoln Psychology Research Ethics Committee (see Appendix A1 for ethical approval form and full details of ethical approval). Participants provided full informed consent and were free to withdraw from the study at any point without providing any motivation, or to withdraw their data at a later point. At the end of the experiment participants were fully debriefed, verbally and in writing (See Appendix B.3 for participant information sheet, consent form and written debrief form).

2.4.3 Three-element test sequences

2.4.3.1 Materials and methods

2.4.3.1.1 Stimuli

Our stimuli for this experiment were identical to those for the auditory experiment, except that the five symbols which formed the basis of our transition matrices were implemented as five shapes, instead of five tones. In the same way as for the auditory experiment, three sets of test sequences were generated: one set of three-element test sequences, one set of five-element test sequences and one set of eight-element sequences.

The same transition matrix as for the auditory study was used (Figure 2.8). The stimuli were a selection of five visual shapes taken from a larger pool which had been successfully used in a number of studies on visual triplet learning (Fiser & Aslin, 2002a; Fiser & Aslin, 2001; Turk-Browne et al., 2005; Turk-Browne & Scholl, 2009). Fiser & Aslin (2002a) judged these shapes to be distinct enough to not be confused with each other.

The same symbolic exposure stream and test sequences were used as for the auditory study. The exposure stream was made up of 909 shapes. Each shape was on the screen for 500 msec with an Inter Stimulus Interval (ISI) consisting in a blank screen, of 100 msec. Therefore, the total duration of the exposure stream was 9.09 minutes. The choice of length of exposure stream was motivated by the need to give participants a similar amount of training between the auditory and visual experiments, whilst at the same time limiting fatigue effects by keeping the amount of exposure to a minimum. In the test phase shapes were presented on the screen at the same pace as during exposure, therefore each of the three-element test sequences had a duration of 1.8 seconds.

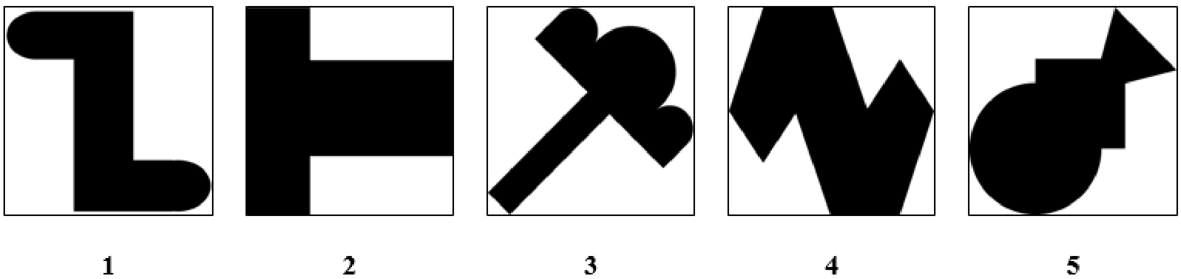

Figure 2.8: Our five shape stimuli representing symbols 1-5 from left to right. The visual display was programmed so that each shape would appear within an imaginary square measuring 1.5 x 1.5 cm, in order to control their size. However, the square outline around each shape is only for illustration purposes in this figure, and was not visible to participants.

2.4.3.1.2 Apparatus

The experimental stimuli and program were programmed using the Psychtoolbox (Brainard, 1997; Pelli, 1997; Kleiner et al, 2007) in MATLAB R2017a, which was also used for the purpose of running the experiment. The experiment ran in one of the testing cubicles at the University of Lincoln on an HP computer with an Intel ® Core ™ i5 vPro processor. The experiment display was presented on an HP 24-inch monitor with a resolution of 1920x1080. Participant responses were collected through a Dell keyboard. The apparatus used was the same for all visual experiments using transition matrix stimuli.

2.4.3.1.3 Procedure

2.4.3.1.4 Exposure phase

Participants were comfortably seated at a distance of approximately 50 cm from the computer screen in a normally-lit testing cubicle. Shapes were presented in black on a white background and were displayed in the centre of the screen enclosed within an imaginary square, of the same size for each shape, which measured 1.5 x 1.5 cm. This way, despite differences in the area of the square occupied by the shapes, the maximal extent of the shapes width-wise and height-wise was kept the same.

In the same way as for the auditory experiment, participants were instructed to watch attentively and no mention was made of the statistical regularities in the exposure stream, or of the presence of a subsequent test phase. On-screen instructions were equivalent to the visual experiment: "You will see a series of shapes. Please watch attentively. Press a key to see the shapes". The exposure phase lasted approximately 10 minutes.

2.4.3.1.5 Test phase

The exposure phase was immediately followed by the test phase. This was identical in nature to the test phase of the auditory experiment, except for the use of the five visual shapes instead of the auditory tones.

2.4.3.2 Results

Similarly to the auditory modality, this pilot experiment's first aim was to establish whether participants acquired sufficient knowledge of the visual sequence structure to allow them to perform above chance in the forced-choice task. Only after establishing above-chance performance we could proceed to test the suitability of the PDP and the guessing/ zero correlation criteria. The proportion of correct responses for participants in this version of the experiment was 0.55 for our first participant and 0.57 for our second participant, both of which were not above individual chance (0.6) We therefore decided to not carry out any further testing for this version of the experiment. As we observed in the case of our auditory transition matrix experiment, a sample of 45 participants would be needed to draw firm conclusions about this result.

2.4.4 Five-element test sequences

2.4.4.1 Stimuli

The visual stimuli for this version of the experiment were the same as for the three-element test sequences version. However, test sequences were five-tones long instead of three, which gave a duration of 3 seconds per test sequences. Three second-order transitions were contained in each five-element test sequence.

2.4.4.2 Procedure

The procedure for this experiment was identical to the three-element test sequences visual version. The only difference was that the test sequences used contained five shapes.

2.4.4.3 Results

For this version of the experiment, we stopped data collection after testing one participant only, whose proportion of correct responses was 0.53, therefore below individual chance This is based on our observation, and the participant’s that the stimuli, and forced-choice task, were too complex for successful performance.

2.4.5 Eight-element test sequences

2.4.5.1 Materials and methods

2.4.5.1.1 Stimuli

In the same way as for the auditory experiment, eight-element test sequences were also tested. These stimuli were identical to those used in the auditory version of the experiment. Each eight-shape test sequence lasted 4.8 seconds.

2.4.5.1.2 Procedure

2.4.5.1.3 Exposure phase

The exposure phase was identical to that of the three and five-element test sequences version.

2.4.5.1.4 Test phase

The exposure phase was immediately followed by a test phase. For this experiment, because the test sequences were deemed too long for participants to be able to hold them in memory, the form of the 2AFC task was changed such that only one structured eight-element test sequence was presented and two last shape alternatives were given, one correctly completing the sequence and the other one incorrectly completing the sequence.

The test phase contained 50 two-alternative forced-choice (2AFC) trials. Each trial consisted of two test sequences, one structured, sharing the same statistical structure as the exposure stream, and one unstructured sequence, which the participant had not heard before. There were 25 individual structured sequences in total, each of which appeared twice during the test, and 50 individual unstructured sequences. The order of presentation of the 50 structured test sequences was randomised such that all 25 structured sequences were presented first, and then a second time. The order of presentation of the 50 unstructured sequences was also randomised.

The two test sequences were presented sequentially. The labels "sequence 1" and "sequence 2" appeared in the centre of the computer screen for the duration of 500 msec before the first and second sequence respectively. No visual stimulus was on screen whilst the tone sequences were playing. There was a 500-msec pause between the end of sequence one and presentation of the "sequence 2" label. In half of the 50 forced-choice trials the structured test sequence was presented first and in the other half the unstructured test sequence was presented first. The order of presentation of the structured and unstructured test sequences within each trial was randomised. Each trial was separated by the next trial by a one-second pause.

In order to assess the conscious status of knowledge with the PDP, the 2AFC task was administered twice: once under inclusion instructions and once under exclusion instructions. On-screen instructions were given at the beginning of each of these two test phases. For the inclusion condition these stated: "Choose which of two sequences is CORRECT. Press Enter to play the sequences", whereas for the exclusion condition instructions were: "Choose which of two sequences is INCORRECT. Press Enter to play the sequences".

A response was required after both the structured and unstructured sequences had been presented. Responses were made by pressing the "1" or "2" number keys in the upper left corner of the computer keyboard. Participants pressed "1" to choose the first sequence that was presented in the 2AFC trial and "2" to choose the second sequence that was presented. On-screen instructions were used on each trial after both the structured and unstructured sequences had been played to prompt the participant to respond and to remind them of the response keys. These appeared on the screen on three separate lines, to ensure clarity: "Respond now", "1 = sequence 1", "2 = sequence 2".

For the purpose of the guessing and zero correlation criteria, confidence and knowledge attribution ratings were collected after each 2AFC trial. For consistency with previous studies (Zoltán Dienes, 2007), confidence ratings were measured on a continuous scale from 50 to 100. At the beginning of the test phase, when given verbal instructions, participants were advised that 50 equated to a guess (this was related by the experimenter to flipping a coin), and 100 was complete certainty in their response (Zoltán Dienes, 2007). After participants had made their 2AFC choice, the following instructions appeared on screen: "How confident are you in your choice? Type in a number 50-100”. Participants used the number keys on the keyboard to make their response. After this, knowledge attribution ratings were collected. On screen instructions asked participants: “What is the basis of your judgement?”. Underneath these instructions, the response keys were detailed: 1 for guess, 2 for intuition, 3 for rules and 4 for memory. Thorough use of the “rules” attribution we aimed to assess the depth of knowledge of transition probabilities in our participants. This is a structural knowledge attribution used in the AGL paradigm (Andy D. Mealor & Dienes, 2013). Participants pressed a key 1-4 to indicate their choice of knowledge attribution. After both confidence and knowledge attribution ratings were collected, a new 2AFC trial was presented. The task was self-paced, with no timeout for any of the responses required.

After participants had completed the 50 2AFC trials for inclusion, the exclusion test was administered. The order of administration of inclusion and exclusion tasks was randomised per participant. Before the beginning of the test phase, both before inclusion and exclusion, participants also received standardised verbal instructions to prepare them for what to expect in the upcoming phase and to explain the meaning of the different knowledge attribution ratings. For the standardised verbal instructions refer to Appendix C. Overall, the test phase lasted approximately 30 minutes.

2.4.5.2 Results

The proportion of correct responses in this version of the experiment was 0.50 for our first participant and 0.48 for our second participant, both under individual chance level (0.6) Based on this outcome, as well as participants’ observations on the complexity of the task, we decided to not carry out any further data collection or analysis. Overall, given the performance results of these three short pilot experiments, indicating that the visual sequence was too complex for participants to successfully perform in the 2AFC task, we did not carry out any further data collection for this study and, instead, turned to exploring alternative methods of testing visual statistical learning using the transition matrix paradigm. It has to be noted, however, that further research using the required minimum sample size of N= 45 would be needed to draw firm conclusions on the presence or absence of a learning effect.

2.4.6 Other approaches to studying visual statistical learning through transition matrix

Given the findings of no learning in our visual experiment versions carried out this far, a number of other pilot investigations were carried out in the visual modality (refer to Table 2.3 for a summary), aiming to establish a suitable way to test visual statistical learning using the transition matrix paradigm. These used a number of variations on the classical transition matrix paradigm and tested different types of visual stimuli. A total of 52 participants were tested for these short pilot experiments.

Experiment version number	Short experiment description	N
1	Dot moving horizontally on the screen. Deterministic transition matrix with 5 symbols, 8-element test sequences.	23
2	Dot moving horizontally on the screen. Reduced probabilistic transition matrix with 4 symbols, 8-element test sequences.	10
3	Dot moving vertically on the screen. Deterministic transition matrix with 5 symbols, 8-element test sequences.	6
4	Deterministic transition matrix with 5 symbols, 8-element test sequences implemented as a colour-changing rectangle, each symbol mapped onto one colour.	9
5	Deterministic transition matrix with 5 symbols, 8-element test sequences implemented as a colour-changing rectangle, each symbol mapped onto one colour – different colour scheme to Version 4.	4

Table 2.3: Summary of pilot investigations conducted using transition matrix stimuli in the visual modality. Table contains an experiment version number, for reference in the sections that follow, a short experiment description and a sample size.

2.4.6.1 Experiment versions 1- 3

2.4.6.1.1 Background

In a Statistical Learning experiment, (Durrant et al., 2016) showed that it is possible for knowledge of statistical regularities to transfer from the auditory to the visual modality. The authors trained participants on auditory stimuli generated through transition matrix very similar to the auditory stimuli which we have used for our auditory experiment in the present chapter. The only two differences between (Durrant et al., 2016)'s stimuli and ours were that our stimuli used a deterministic transition matrix and 8-element test sequences, whilst the authors used a probabilistic transition matrix, therefore of a higher level of difficulty than ours, and 18-element test sequences. (Durrant et al., 2016)'s test phase was in the visual modality, and consisted of 18-element test sequences, implemented as horizontal locations on the computer screen, giving the illusion of a travelling circle. To mirror the five tones which formed the basis of the auditory stimuli, the authors used five vertical locations on the screen, where each location corresponded to one tone from lowest to highest in pitch. Results showed that participants trained with the auditory stimuli, could apply their acquired knowledge of the statistical structure to the visual stimuli, despite being naïve to the analogy between the auditory and visual stimuli. This work formed the basis of our experiment version 1, which bears many similarities with (Durrant et al., 2016)'s work. We reasoned that our participants would be able to learn the statistical structure of visual stimuli generated through a transition matrix, if implemented as a travelling circle which moved across five vertical locations.

Our experiment versions 2 and 3 were based on findings of statistical motor learning, using the SRTT paradigm. Participants have, in fact, been shown to be able to learn the statistical structure of second-order conditional sequences purely perceptually, by watching the sequence on the computer screen implemented as one of four empty squares filling at a time following the order of the sequence (Heyes & Foster, 2002). Given that our transition matrix also uses second-order statistics, we thought that participants would be able to learn the statistical structure of visual stimuli, if each element, or symbol, forming the basis of our transition matrix was implemented as one of five vertical or horizontal locations on the computer screen. Crucially, in their study, (Heyes & Foster, 2002) showed that perceptual information is enough for participants to learn the training sequence, and that this knowledge was acquired in the same way as when participants responded to each cue, or movement, on the screen, as in the standard SRT task.

2.4.6.1.2 Materials and methods

<u>*Experiment version 1*</u>

Participants

Twenty participants were tested for the purpose of this experiment. Age and gender data were not collected, but there were no age restrictions for taking part. All participants were undergraduate and postgraduate students at the University of Lincoln, some participating in exchange for research credit points and some participating, for no reward, upon invitation by the experimenter. All participants had normal or corrected-to-normal vision. No participant had any medical conditions which could have affected his/ her participation, or the validity of the data.

Stimuli

The stimuli for this experiment were generated using the same deterministic transition matrix as the one used in our auditory study with eight-element test sequences. However, following on from (Durrant et al., 2016), the five symbols were implemented as a yellow circle moving across five vertical locations on the screen and the temporal dimension was implemented as eight horizontal locations across the screen. Although, differently to (Durrant et al., 2016), this was not a cross-modal experiment, following on from these authors, we implemented these stimuli to be the visual analogous of our successful auditory transition matrix experiment. The eight horizontal locations also matched the number of elements within each test sequence. The yellow circle moved from left to right on a black background on a screen with a resolution of 1366 x 768 pixels. It started its movement from a location 173 pixels from the left edge of the screen and remained at that location for 400 msec before reappearing, after being off screen for 20 msec, in its next location 141 pixels to the right and remaining at that location for 400 msec. The circle moved to the right through all the 8 horizontal locations before starting its cycle again at the leftmost position on the screen. Through this setup, therefore, the circle appeared to be moving across the screen. Depending on the specific symbol of the sequence, throughout its trajectory, the circle occupied one of five equally spaced vertical locations. The top vertical location was 218 pixels from the margin of the screen and each of the subsequent four locations was placed 92 pixels underneath this. The yellow circle occupied 20 x 21 pixels.

Apparatus

MATLAB R2017a was used to program and run the experiment, with the aid of the Psychtoolbox (Brainard, 1997; Pelli, 1997; Kleiner et al, 2007). The experiment took place in one of the testing cubicles at the University of Lincoln on an HP computer with an Intel ® Core ™ i5 vPro processor. The experiment display was presented on an HP 24-inch monitor with a resolution of 1920x1080. Participant responses were collected through a Dell keyboard.

Procedure

Exposure phase

The exposure phase was identical to that of our auditory experiment in this chapter which used eight-element test sequences, and used the same symbolic exposure sequence, with the exception that instructions were adjusted to reflect the difference in stimuli. Participants were told that they would see a yellow dot travelling across the screen and to watch attentively. Participants viewed the stimuli at a distance of 50 cm from the screen. The exposure phase lasted just over 7 minutes.

Test phase

The test phase was identical to that of our auditory transition matrix experiment, and therefore used eight-element test sequences with the exception that the on-screen instructions were changed to "choose which of the two movement sequences is correct", for inclusion and "choose which of the two movement sequences is incorrect" for exclusion, to reflect the difference in stimuli. As part of the PDP, both inclusion and exclusion conditions were tested in the same way as our auditory experiment. However, we administered inclusion first and exclusion second in this version of the experiment and the last six participants in our sample did not take part in the exclusion condition, as the primary goal was to evaluate whether inclusion performance would be above chance in this task.

Experiment version 2

Participants

Ten participants were tested for this experiment version. Age and gender data were not collected, but there were no age restrictions for taking part. All participants were undergraduate and postgraduate students at the University of Lincoln, some participating in exchange for research credit points and some participating, for no reward, upon invitation by the experimenter. All participants had normal or corrected-to-normal vision. No participant had any medical conditions which could have affected his/ her participation, or the validity of the data.

Stimuli

Stimuli for this experiment were similar to those of experiment version 1, with the exception that, in order to decrease task difficulty, and aiming to find whether above-chance performance was possible, we used a reduced transition matrix based on four, instead of five, symbols (Figure 2.9).

	1	2	3	4
11	0.033333	0.033333	0.033333	0.9
12	0.9	0.033333	0.033333	0.033333
13	0.033333	0.033333	0.9	0.033333
14	0.033333	0.9	0.033333	0.033333
21	0.9	0.033333	0.033333	0.033333
22	0.033333	0.033333	0.9	0.033333
23	0.033333	0.9	0.033333	0.033333
24	0.033333	0.033333	0.033333	0.9
31	0.033333	0.9	0.033333	0.033333
32	0.033333	0.033333	0.033333	0.9
33	0.9	0.033333	0.033333	0.033333
34	0.033333	0.033333	0.9	0.033333
41	0.033333	0.033333	0.9	0.033333
42	0.033333	0.9	0.033333	0.033333
43	0.033333	0.033333	0.033333	0.9
44	0.9	0.033333	0.033333	0.033333

Figure 2.9: Reduced probabilistic transition matrix based on four symbols.

Similar to Version 1, we implemented the four symbols as four vertical locations on the screen, with the temporal dimension implemented as eight horizontal locations, which also matched with the eight elements contained in each test sequence. In this experiment version the colour of the circle was changed to dark grey, and presented on a light grey background, for ease of visual processing. The screen resolution was 1366 x 768 pixels, and the screen started its movement from a location 250 pixels from the left edge of the screen, and remained at that location for 200 msec before reappearing in its next location 121 pixels to the right. In-between locations, the dot was off screen for 20 msec. In this experiment version we increased the speed of visual presentation, using a 200-msec stimulus presentation, compared to 400 msec in experiment version 1, to assess whether a faster speed would aid retention of the sequence in memory. In terms of the four vertical locations, representing the sequence symbols, the top vertical location was 184 pixels from the top margin of the screen, and each of the subsequent four locations was 140 pixels underneath this.

Apparatus

Apparatus information was the same for all pilot experiments in this series. Please refer to the Apparatus section of experiment version 1.

Procedure

Exposure phase

The exposure phase was identical to that of experiment version 1, with the exception that, with the reduced stimulus presentation time, it lasted approximately four minutes.

Test phase

The test phase was identical to experiment version 1, except for the number of test sequences which changed to reflect the reduced transition matrix. There were 16 possible “active”, or structured, test sequences, therefore the experiment was made of 32 trials, as each active test sequence was presented twice. The “passive”, or unstructured, condition contained 32 unique test sequences.

Experiment version 3

Participants

Six participants were tested for this experiment version. Age and gender data were not collected, but there were no age restrictions for taking part. All participants were undergraduate and postgraduate students at the University of Lincoln, some participating in exchange for research credit points and some participating, for no reward, upon invitation by the experimenter. All participants had normal or corrected-to-normal vision. No participant had any medical conditions which could have affected his/ her participation, or the validity of the data.

Stimuli

This experiment used the same deterministic transition matrix as experiment version 1, based on five elements. The same visual stimuli were used as experiment version 2, consisting in a dark grey circle presented on a grey background, which travelled, aligned with the centre of the screen, through five vertical locations, representing, from lowest to highest, symbols 1-5 used by our transition matrix. Symbol 1 was represented by the lowest location, which was 626 pixels from the bottom hedge of the screen and aligned centrally. The next location up (symbol 2) was 125 pixels higher than the location for symbol 1, and so on, in steps of 125 pixels through to symbol 5. The grey circle remained in its location for 200 msec. There was a 100-msec gap, with no circle on the screen, in-between transitions.

Apparatus

Apparatus information was the same for all pilot experiments in this series. Please refer to the Apparatus section of experiment version 1.

Procedure

Exposure phase

The exposure phase was identical to that of our auditory experiment using eight-element test sequences, and used the same symbolic exposure sequence, with the exception that instructions were adjusted to reflect the difference in stimuli. Participants were told that they would see a dot moving between five vertical locations, and to watch attentively. The exposure phase lasted just under 6 minutes.

Test phase

The test phase was identical to that of our auditory transition matrix experiment using eight-element test sequences, with the exception that the on-screen instructions were changed to "choose which of the two movement sequences is correct", for inclusion and "choose which of the two movement sequences is incorrect" for exclusion to reflect the difference in stimuli. As part of the PDP, both inclusion and exclusion conditions were tested in the same way as our auditory experiment. However, we administered inclusion first and exclusion second in this version of the experiment and the last six participants in our sample did not take part in the exclusion condition, as the primary goal was to evaluate whether inclusion performance would be above chance in this task.

2.4.6.1.3 Results

Performance results of the three visual pilot experiments are summarised in Table 2.4. Inclusion performance was found to be at chance level (0.5) in Version 1, but participants performed significantly above chance in Version 2 and Version 3 under inclusion and either significantly below chance (Version 2) or at chance (Version 3) under exclusion, both of which indicate that participants' knowledge was held explicitly.

Experiment version	**N**	**Inclusion performance**	**one-sample t-test (inclusion)**	**Exclusion performance**	**one-sample t-test (exclusion)**
1	17	M = 0.52 (SD = 0.07)	*p* = .145, one-tailed, Cohen's *d* = 0.266	M = 0.48 (SD = 0.05)	*p* = .058, two-tailed Cohen's *d* = 0.494
2	10	M = 0.59 (SD = 0.08)	*p* = .008, one-tailed Cohen's *d* = 1.097	M = 0.41 (SD = 0.09)	*p* = .017, two-tailed Cohen's *d* = 0.923
3	6	M = 0.56 (SD = 0.04)	*p* = .003, one-tailed Cohen's *d* = 1.460	M = 0.49 (SD = 0.04)	*p* = .444, two-tailed Cohen's *d* = 0.339

Table 2.4: Mean proportion of correct responses in the 2AFC task for each experiment version and one-sample t-test results against chance level (0.5) separately for inclusion and exclusion conditions.

To further evaluate the presence of explicit knowledge, we carried out paired-samples t-tests between the proportion of structured sequences chosen in the 2AFC task under inclusion and exclusion conditions. According to the PDP, a significantly higher proportion of structured sequences under inclusion than exclusion is indicative of explicit knowledge.

For experiment version 1, we found no difference between the proportion of structured sequences chosen under inclusion and exclusion, $t(16) = 1.919$, $p = .073$, Cohen's $d = 0.465$, 95% Cis of the difference [-0.004 0.087]. However, this difference was significant for experiment version 2, $t(9) = 3.442$, $p = .007$, Cohen's $d = 1.088$, 95% Cis of the difference [0.062 0.300], and for experiment version 3, $t(5) = 6.220$, $p = .002$, Cohen's $d =$, 95% CIs of the difference [0.041 0.099].

Despite the above-chance average observed for experiment version 1 and version 2, upon examination of the raw data, individual performance was deemed to be too low to use these experiments as the basis for an investigation of implicit and explicit knowledge in visual statistical learning. This decision was also informed by the observation of wide individual differences in the data, with only a few individuals performing well in the task. Given the overall low performance, we set out to investigating stimuli in the visual modality using colours instead.

2.4.6.2 Experiment version 4– 5

2.4.6.2.1 Background

The choice of type of stimuli for experiment versions 4-5 was motivated by (Conway & Christiansen, 2009)' s Artificial Grammar Learning (AGL) study, which implemented an artificial grammar built on the basis of five unique elements as different-colour squares appearing sequentially in the centre of the computer screen. Our rationale was that, if participants were able to acquire the statistical structure of the stimuli in (Conway & Christiansen, 2009)' s study, they should be able to learn statistically-structured stimuli generated through our transition matrix and implemented as colours.

2.4.6.2.2 Materials and methods

Experiment version 4

Participants

Nine participants were tested for this experiment version. Age and gender data were not collected, but there were no age restrictions for taking part. All participants were undergraduate and postgraduate students at the University of Lincoln, some participating in exchange for research credit points and some participating, for no reward, upon invitation by the experimenter. All participants had normal or corrected-to-normal vision. No participant had any medical conditions which could have affected his/ her participation, or the validity of the data such as, for example, colour blindness.

Stimuli

We generated the stimuli for the experiment using the same deterministic transition matrix as the one used in our auditory study with eight-element test sequences. Each of the five symbols in the transition matrix was implemented as one colour. Each coloured rectangle measured 150 x 100 pixels and remained on the screen for 200 msec before switching to the next colour after a 100 msec gap. Colours were presented on a black background.

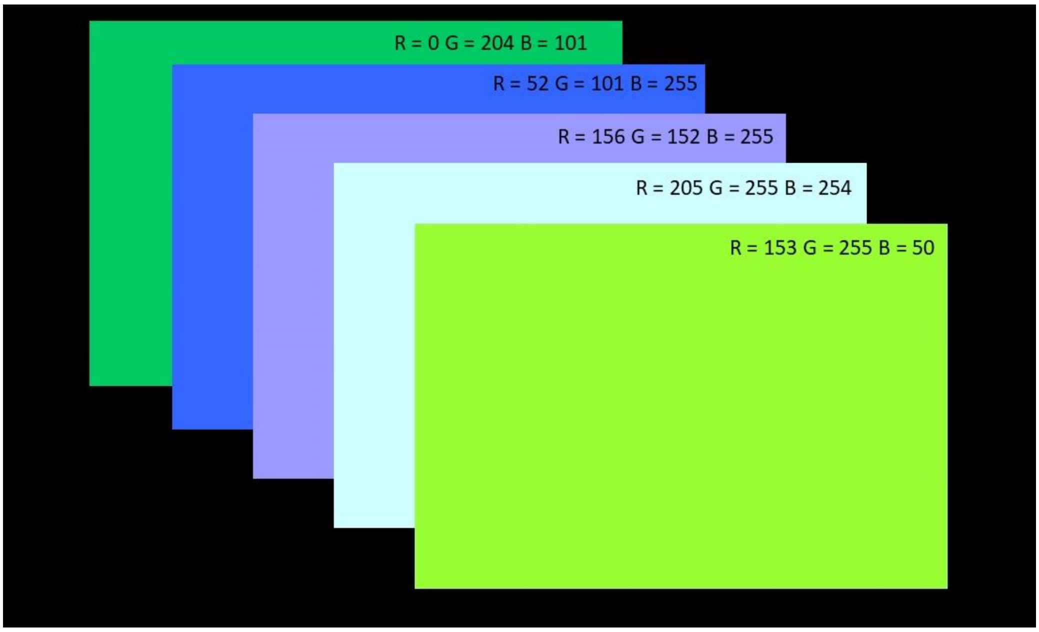

Figure 2.10: Colour stimuli corresponding, from left to right, to symbols 1- 5 used by the deterministic transition matrix and their RGB values.

Apparatus

Apparatus information was the same for all pilot experiments in this series. Please refer to the Apparatus section of experiment version 1.

Procedure

Exposure phase

The exposure phase was identical to that of our auditory transition matrix experiment. Instructions were adjusted to reflect the difference in stimuli, and participants were instructed that they would see a square in the centre of the screen which would change in colour, and to watch attentively. The exposure phase lasted just under 6 minutes.

Test phase

The test phase was identical to that of our auditory transition matrix experiment using eight-element test sequences, with the exception that the on-screen instructions were changed to “choose which of the two colour sequences is correct”, for inclusion and “choose which of the two colour sequences is incorrect” for exclusion to reflect the difference in the stimuli.

Experiment version 5

Participants

Six participants were tested for this experiment version. Age and gender data were not collected, but there were no age restrictions for taking part. All participants were undergraduate and postgraduate students at the University of Lincoln, some participating in exchange for research credit points and some participating, for no reward, upon invitation by the experimenter. All participants had normal or corrected-to-normal vision. No participant had any medical conditions which could have affected his/ her participation, or the validity of the data, such as, for example, colour blindness.

Stimuli

The stimuli were identical to those of our colour experiment version 4, except for differences in the colour scheme. Colours were presented on a grey background for ease of visual processing and were equated for brightness, in order to prevent one particular sequence element from standing out (Figure 2.11).

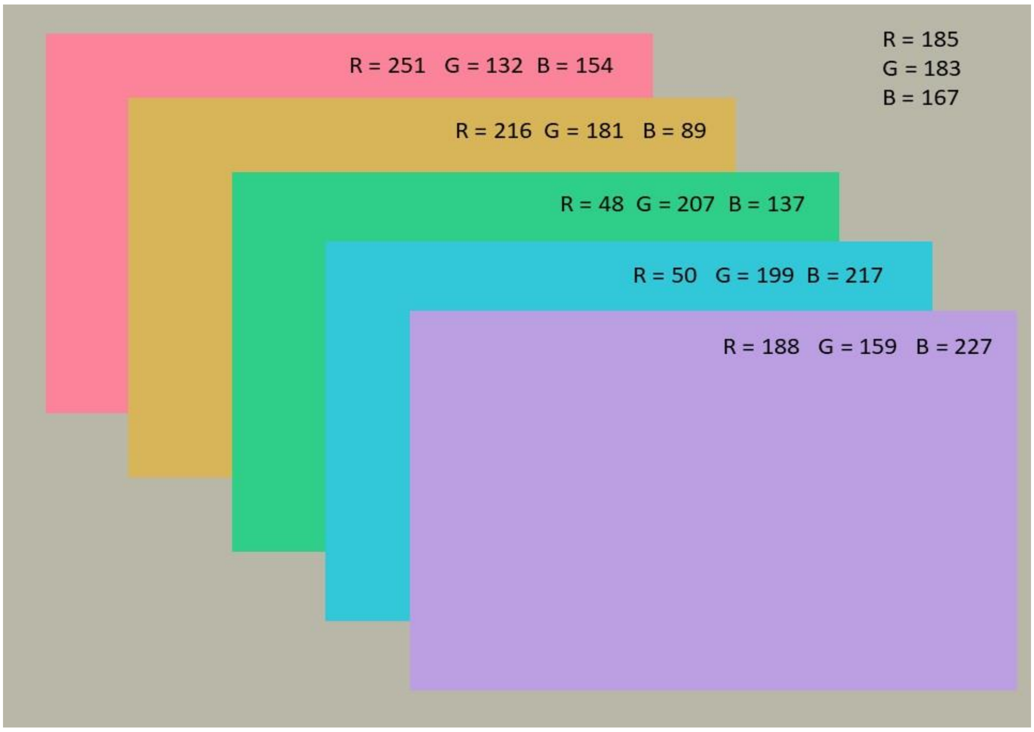

Figure 2.11: Colour stimuli corresponding, from left to right, to symbols 1-5 used by the deterministic transition matrix and their RGB values, including RGB values for the grey background.

Apparatus

Apparatus information was the same for all pilot experiments in this series. Please refer to the Apparatus section of experiment version 1.

Procedure

The procedure of this experiment version was identical in all its parts to the colour experiment version 4, except for differences in the colour scheme used.

2.4.6.2.3 Results

Performance results of the two colour experiments are summarised in Table 2.5. Both inclusion and exclusion performance were at chance level (0.5) in both experiment versions, indicating that participants had not acquired knowledge of the statistical regularities expressed through colour changes. Paired-samples t-tests between the proportion of structured colour sequences chosen under inclusion and exclusion were not carried out on this occasion, as they were not meaningful, in the context of at-chance inclusion performance.

Experiment version	N	Inclusion performance	one-sample t-test (inclusion)	Exclusion performance	one-sample t-test (exclusion)
4	9	*M* = 0.50 (*SD* = 0.13)	*p* = .480, one-tailed Cohen's *d* =0.017	*M* = 0.51 (*SD* = 0.13)	*p* = .838, two-tailed Cohen's *d* =0.070
5	4	*M* = 0.59 (*SD* = 0.11)	*p* = .093, one-tailed Cohen's *d* = 0.856	*M* = 0.44 (*SD* = 0.06)	*p* = .134, two-tailed Cohen's *d* = 1.019

Table 2.5: Mean proportion of correct responses in the 2AFC task for each experiment version and one-sample t-test results against chance level (0.5) separately for inclusion and exclusion conditions.

2.4.7 Conclusions regarding transition matrix stimuli in the visual modality

Overall, this series of pilot experiments using visual stimuli generated through a transition matrix showed that participants are not able to learn the visual statistical regularities to a degree that allows them to successfully perform in a forced-choice task. Average performance in these tasks was deemed too low to provide a solid basis for the investigation of questions regarding implicit and explicit knowledge. In particular, based on our observation of the raw data, we deemed variability between participants to be too high, as we aimed to achieve more consistent performance in our investigations of the visual modality.

Our failure to find above-chance learning in experiment version 1 was surprising, given that participants in Durrant et al.'s 2016 study were able to express their knowledge in a forced choice task with the same setup as our experiment. However, participants in that study had learned the statistical structure of the stimuli in the auditory modality originally, and only after transferred this knowledge to the visual modality. This suggests that there are constraints as to the type of structure that can be learned in the visual modality.

Our experiment Version 2 in this series of pilot experiments showed that using a reduced transition matrix, based on four elements instead of five, results in higher performance by participants. However, reducing the number of elements that formed the transition matrix led to a high number of same-element repetitions in this experiment version. Although the number of repetitions can be limited to a certain extent in the production of such stimuli, same-element repetitions cannot be completely eliminated in this paradigm. We reasoned that a high number of same-element repetitions within the stimuli could interfere with the measurement of statistical learning, as participants could use the presence or absence of these repetitions to help them discriminate between trained and untrained test fragments, and therefore their performance would be based more heavily on strategies and less on genuine learning of the statistical structure of the stimuli.

The performance improvement when using a reduced transition matrix might suggest that working memory constraints are potentially responsible for the low performance in our participants. This poses a methodological challenge for the use of transition matrix stimuli due to the fact that reducing the number of elements which form the basis of the matrix increases the number of same-element repetitions present in the stimuli. This might negatively affect the measurement of knowledge in this paradigm, as mentioned above.

Overall, these data led us to the decision to abandon the use of the transition matrix paradigm for the study of implicit and explicit learning. This motivated our choice to investigate the use of the PDP and guessing and zero correlation criteria in a visual Triplet Learning paradigm in the next chapter.

2.5 General conclusions

This chapter aimed to establish whether visual and auditory statistical learning stimuli generated through a transition matrix are suitable for the investigation of the question of implicit and explicit knowledge. We also aimed to test the suitability of the PDP and the guessing and zero correlation criteria for the measurement of the status of knowledge in this paradigm. Our data show that our methods for the measurement of conscious knowledge can be successfully used with transition matrix stimuli in the auditory modality. In this modality, we found successful learning in both adults and children, and our data indicate that both age groups acquire explicit knowledge of the stimuli. In contrast, we discovered that visual stimuli generated through a transition matrix are too difficult for participants to be able to successfully express this knowledge in a forced-choice task, and, consequently, this paradigm cannot be used for the investigation of implicit and explicit knowledge in this modality. This led to the decision to abandon the use of transition matrix stimuli in the visual modality and motivated our investigations in the next chapter.

Chapter 3 Triplet Learning

3.1 Introduction

Our investigations in Chapter 2 showed that participants were unable to achieve above-chance performance when tested on their learning of statistically structured stimuli generated through transition matrix in the visual modality. Therefore in this study we aimed to find a statistical learning paradigm that would produce stimuli which our participants could learn in both modalities, in order to investigate the two in parallel. Very little research has assessed the use of PDP and guessing and zero correlation criteria with triplet learning, therefore it was necessary to establish their validity as a measure of conscious knowledge for this paradigm. This chapter investigated implicit and explicit knowledge in a triplet learning paradigm in the visual and auditory modality.

In the triplet learning task, which was first introduced by Saffran, Aslin, & Newport (1996) for the study of language acquisition mechanisms, unbeknownst to participants, individual items in the exposure stream are grouped into triplets. Typically, after a familiarisation phase where no mention is made of the presence of statistical regularities, participants are administered a surprise forced-choice task. Within this, each trial presents two triplets: one from the familiarisation stream and another foil triplet, made of a combination of shapes which have never appeared together before. The transition probabilities between shapes within a foil triplet are zero. Typical findings are that exposure triplets are identified correctly over foil triplets, which means that group performance is above chance, 50% in a two-alternative forced-choice (2AFC) task. This finding, first obtained by Saffran, Aslin, & Newport (1996) using a purpose-built language, has been replicated not only in the domain of artificial speech (Jenny R. Saffran et al., 1997; Graf et al., 2007; Eigsti, 2012; Franco et al., 2011b), but also in the processing of tone stimuli (Saffran, Johnson, Aslin, & Newport, 1999; Creel et al., 2004), visual shapes (Kirkham et al., 2002; Fiser & Aslin, 2002a; Turk-Browne et al., 2005; Schapiro et al., 2014), and even tactile sequences (Conway & Christiansen, 2005).

Traditionally, this type of statistical learning has been considered a form of implicit learning, to the point that the terms statistical learning and implicit learning have been often used interchangeably (Pierre Perruchet & Pacton, 2006). This implicitness assumption has been based on the incidental nature of the acquisition (Fiser & Aslin, 2001; Fiser & Aslin, 2005), the presence of this kind of learning in infants (Saffran et al., 1996; Fiser & Aslin, 2002c; Aslin et al., 1998; Graf et al., 2007; Kirkham et al., 2002; Bulf et al., 2011) and non-human primates (Hauser et al., 2001; Goujon & Fagot, 2013; Rakoczy et al., 2014) and suggestions that this learning does not need focused attention to take place, and therefore participants display learning even when a secondary task is present during exposure (Jenny R. Saffran et al., 1997). Despite these characteristics that have been observed have led to the belief that this learning is implicit, that is, a process that takes place outside of conscious awareness, not much research has focused on testing this assumption experimentally, by actually measuring the conscious status of knowledge, that is, whether participants are aware of the knowledge they have acquired. Only a limited number of studies has reported information on participants' awareness of the acquired knowledge. These have often relied on informal verbal reports in which participants are asked whether they had realised about the patterns present in the input stimuli and whether they were aware of the relationships between elements (Fiser & Aslin, 2001; Saffran et al., 1999; Fiser & Aslin, 2005; Conway & Christiansen, 2005). Participants' inability to report information about the stimulus structure, alongside an ability to perform above chance in the forced-choice test, has been interpreted as implicit knowledge (Fiser & Aslin, 2001; Saffran et al., 1999; Fiser & Aslin, 2005). When considering studies which had the measurement of implicit and explicit knowledge as one of their primary interests, some suggest that the acquired knowledge of the triplets is held explicitly (Bertels, Boursain, Destrebecqz, & Gaillard, 2015b), and that participants are able to control the knowledge they have acquired (Franco et al., 2011b), whilst some do not find any evidence of conscious knowledge, (Kim et al., 2009). Therefore, there remains ambiguity in the literature as to the status of the acquired knowledge in a triplet learning paradigm, both for the visual and auditory modality. As the results obtained with regards to implicit and explicit knowledge in sequential regularities learning are understood to be critically dependent on the approach taken to measuring conscious knowledge (Seth et al., 2008), a position that we share, we argue that an adequate methodology is essential in order for research on this topic to progress.

In a visual triplet learning paradigm, using four triplets created by arranging 12 unique shapes into four groups of three, Kim et al., (2009) assessed explicit knowledge through a "matching questionnaire", which was designed to assess whether participants knew which three shapes were grouped together. Participants were presented with one shape and were asked to choose from the remaining 11 shapes which two they thought were associated with it. Although this completion task was considered a test of explicit knowledge, we argue that this test is potentially subject to contamination by implicit knowledge. In fact, correct choice of two of the shape alternatives by participants does not necessarily have to be accompanied by an awareness that the knowledge is being held but could, instead, be the result of more implicit knowledge, such as a feeling of intuition, unaccompanied by awareness. Furthermore, although it is possible that both implicit and explicit knowledge may be present on any given trial, the matching questionnaire task does not provide a way of teasing apart the contribution of implicit and explicit influences on task performance.

Along with other authors (Fu et al., 2013), we support the use of PDP as a valid measure to separate conscious and unconscious knowledge and argue that the PDP has not been used enough in the context of the triplet learning paradigm. Franco et al., (2011b) have previously applied the PDP with artificial language stimuli which contained artificial "word" units made of three syllables. The authors used a yes/ no form of the 2AFC task in their implementation of the PDP. As part of this, participants were trained on two artificial languages and, during the test phase, they were presented with one "word" (or syllable triplet) at a time. Under inclusion, they were asked to respond "yes" to training words and "no" to new words, whilst, under exclusion, they were asked to endorse, by responding "yes", words from only one of the two training languages, and to reject, by responding "no" words from the other training language, along with new words. Based on the logic of the PDP, control was required by participants for them to be able to reject (say "no" to) training words.

We suggest that statistical learning research would benefit from a form of 2FAC Task in which both triplets, a training triplet and a new triplet, are presented on each trial. This could be a more sensitive measure of participants' control over their knowledge, as, under exclusion, when asked to choose the "less familiar" triplet, they are required to discriminate between a training triplet and a new triplet, which makes their choice mode informed, therefore minimising the possibility for random guessing. Furthermore, to the best of our knowledge, no research has applied the PDP in a triplet learning paradigm using shape or tone stimuli. Given our successful use of the PDP with a 2AFC task in the auditory modality in our Chapter 2 of this thesis, we set out to follow the same procedure in this study, by testing our participants' knowledge through the administration of a 2AFC task twice: once under inclusion instructions and once under exclusion instructions.

More recent work on visual triplet learning has suggested that participants are consciously aware of the statistical regularities acquired in this task (Bertels et al., 2015a). This evidence, however, is solely based on the use of the binary confidence ratings (guess and remember), and their relationship to accuracy in a forced-choice task, for the purpose of the guessing criterion. We are aware, however, that subjective ratings of confidence are subject to individual bias (Dienes, 2007), and therefore we discourage their use on their own, without the concurrent use of an objective measure of conscious knowledge. Instead, following a similar methodology to that of our Chapter 2 of this thesis, in this study we combined the use of the PDP with the guessing and zero correlation criteria. We expected that the combination of these two measures would also be useful from a methodological viewpoint, as it would allow us to evaluate the extent to which they produce similar results.

Whilst most of the research that is close to the present study in terms of aims and methodology has focused on either triplet learning in the visual modality, or artificial language, less work has been done with auditory tones. We argue that studying not only different input modalities but also different types of stimuli, which might less closely resemble natural language, is important for the understanding of the statistical learning ability and, specifically, the extent to which the learning mechanisms are domain general, in the sense that they can operate on various types of input (Kim et al., 2009). As well as addressing the question of conscious awareness, we believed that the data obtained in this study would also contribute to our understanding of the domain generality or specificity of statistical learning.

In this study, we aimed to replicate findings of visual triplet learning, using shape stimuli and auditory triplet learning using tone stimuli, as well as extend current knowledge by assessing awareness through a combination of objective and subjective measures. Based on the existing evidence, we expected participants to be able to learn in both modalities. Given the lack of previous work which uses our same methodology, we considered the status of the acquired knowledge in visual and auditory triplet learning to be an open question.

3.2 Auditory triplet learning

3.2.1 Materials and methods

3.2.1.1 Participants

Thirty-five participants took part in the experiment. Participants were a mixture of undergraduate and postgraduate students at the University of Lincoln, or members of the public. Whilst undergraduate students took part in the experiment in exchange for research credit points, the other participants received a cash compensation worked out on the basis of £10 hourly rate for research participants. Twenty participants were randomly allocated to the Language 1 group, and 15 participants were allocated to the Language 2 group. Demographic information was missing for eight participants. Of the participants for which full demographic information was present, fourteen were males (age range = 19-37 years, mean age = 23.71, *SD* = 5.64) and thirteen were females (age range = 18-39 years, mean age = 22.31, *SD* = 5.47). One participant had a diagnosis of dyslexia. All participants had normal or corrected to normal vision and no medical conditions which could have affected their participation or the validity of the data. Nineteen participants spoke English as their first language and nine participants spoke English as their second language.

3.2.1.2 Ethics

The study received ethical approval from the University of Lincoln Psychology Research Ethics Committee (see Appendix A for ethical approval form and full details of ethical approval). Participants provided full informed consent and were free to withdraw from the study at any point without providing any motivation, or to withdraw their data at a later point. At the end of the experiment participants were fully debriefed, verbally and in writing (See Appendix D.1 for participant information sheet, consent form and written debrief form).

3.2.1.3 Stimuli

We utilised “tone words”, or triplets, from Saffran et al's 1999 research. The authors used a two-language design, whereby two separate “tone languages” made up of distinct sets of triplets are created, and participants are randomly allocated to training with either Language 1 (L1) or Language 2 (L2). This is for the purpose of mutual control between the two languages, to ensure that any learning obtained in the task is a genuine effect, not attributable to biases towards or against certain arrangements of tones. Data for the L1 and L2 participant groups is then pooled for analysis. Intending to make use of the two-language design in this experiment, we selected four out of the total six triplets from L1 and four triplets from L2 of (Saffran et al., 1999). Starting at middle C, our Language One (L1) consisted of triplets ADB, DFE, FCF$^{\#}$, D$^{\#}$ED and Language Two (L2) consisted of triplets AC$^{\#}$E, F$^{\#}$G$^{\#}$E, C$^{\#}$BA, G$^{\#}$BA. The two languages used 10 pure tones in total, which were sampled in Matlab R2017a at a frequency of 11025 Hz. For a representation of the full chromatic scale used by Saffran et al., (1999), containing the notes used for the four triplets in the present experiment, refer to Figure 3.1. Given Saffran et al’s findings of no significant difference in performance between the two tone languages, which led to the assumption that all triplets were equally appropriate for this statistical learning task, we selected our four triplets for each language randomly out of (J R Saffran's six triplets. Our choice of only four triplets was to match other visual statistical learning studies (Fiser & Aslin, 2002a; Fiser & Aslin, 2001; Turk-Browne et al., 2005; Turk-Browne & Scholl, 2009), as well as our own visual triplet learning experiment, detailed later on in this chapter.

Freq (Hz)	261.63	277.18	293.66	311.13	329.63	349.23	369.99	391.99	415.30	440	466.16	493.88
Note	c	$c^{\#}$	d	$d^{\#}$	e	f	$f^{\#}$	g	$g^{\#}$	a	$a^{\#}$	b

Figure 3.1: A representation of the chromatic scale used for our tone triplets, note names, and their corresponding frequencies in Hz.

3.2.1.4 Apparatus

The experimental stimuli and program were programmed using the Psychtoolbox (Brainard, 1997; Pelli, 1997; Kleiner et al, 2007) in MATLAB R2017a, which was also used for the purpose of running the experiment. The experiment ran in one of the testing cubicles at the University of Lincoln on an HP computer with an Intel ® Core ™ i5 vPro processor. The experiment display was presented on an HP 24-inch monitor with a resolution of 1920x1080. Participant responses were collected through a Dell keyboard, and sound stimuli were played in stereo mode through a pair of headphones.

3.2.1.5 Procedure

3.2.1.5.1 Exposure phase

In the same way as previous auditory triplet learning studies (Saffran et al., 1999), the exposure stream was formed by randomly concatenating tone words, from L1 or L2, to form a continuous tone sequence so that the transition probabilities between tones within a triplet were higher than those between tones across triplet boundaries. Triplets were concatenated with two constraints: no same-triplet repetitions were allowed and no repetitions of pairs of triplets. The exposure stream consisted of 288 tones (trials), or 96 triplets. Each of the four triplets was repeated 24 times during exposure, which is a larger amount of training for each triplet than given in Saffran et al., (1999), where each of the six triplets was repeated 18 times during exposure. However, our primary goal was to match our auditory and visual experiment versions, therefore in this auditory experiment we administered the same amount of training as our later visual experiment. To match Saffran et al's (1999) auditory presentation, each of our tones had the same duration of 0.33 seconds with no gaps between tones, therefore our exposure stream was 1.5 minutes long. Half the participants were trained on the L1 exposure stream and the other half were trained on the L2 exposure stream.

Before the start of the experiment, in the same way as for our first auditory experiment, participants were asked to wear the headphones and set the volume to a comfortable level. The same instructions were administered to participants as our previous auditory experiment using transition matrix: "You will hear a sequence of tones. Please listen attentively. Press a key to play the tones". No mention was made of the statistical regularities in the exposure stream or that there would be a test phase afterwards.

3.2.1.5.2 Test phase

The 2AFC was administered immediately after exposure. There were 32 2AFC trials, each consisting of two triplets, one from L1 and the other from L2. All four triplets from each of the two languages were paired with one another so that all possible combinations of L1 and L2 triplets appeared in the 32 2AFC test trials. The order of presentation of L1 and L2 triplets in each 2AFC test trial was counter-balanced so that in half of the test trials a triplet from L1 was presented first and in the other half of test trials a triplet from L2 was presented first.

Participants in both language groups were presented with the same test trials. However, the training triplets for the participants trained on L1 were unseen triplets for the participants trained on L2 and the training triplets for the participants trained on L2 were unseen triplets for the participants trained on L1. Therefore, the correct response on each trial depended on whether the specific participant had been trained on L1 or L2. The 32 test trials contained 8 repetitions of each of the four triplets, from L1 and from L2. The order of test trials was randomised per participant.

The 2AFC task was almost identical to that of our previous transition matrix experiment. The two auditory triplets were presented sequentially and preceded by the labels “sequence 1” and “sequence 2” appearing on screen for 500 msec before the first and second auditory triplet, respectively. Whilst the auditory triplets were being played there was no visual stimulus on screen. As each tone lasted 0.33 seconds, each auditory triplet had a duration of almost one second. There was a 500-msec pause between the end of the first test sequence and presentation of the “sequence 2” label. There was a one-second pause between trials.

As in our previous auditory experiment, the PDP was used to assess the conscious status of knowledge, therefore our 2AFC task was administered twice: once under inclusion instructions and once under exclusion instructions. The only difference in the administration of the PDP between this experiment and our previous auditory experiment carried out in Chapter 2 was that inclusion instructions were changed to “choose which of the two sequences sounds more familiar” and exclusion instructions were changed to “choose which of the two sequences sounds less familiar”. This is in contrast to our instructions in Chapter 2 which stated “choose which of the two sequences is correct” and “choose which of the two sequences is incorrect”. We thought that emphasising familiarity within participant instructions would be more appropriate for our task, in that it would encourage participants to use a range of knowledge attributions. The order of administration of inclusion and exclusion tasks was randomised per participant.

The same on-screen instructions as our transition matrix experiment were used to prompt participant response. Responses were made by pressing the “1” key on the top left corner of the keyboard to choose the first triplet that was presented and the “2” key to choose the second triplet that was presented. Confidence and knowledge attribution ratings after each 2AFC trial were collected in the same way as our transition matrix experiment. The only change was that knowledge attribution ratings were changed to guess, intuition, memory or other. We reasoned that the “rules” attribution used in our Chapter 2 of this thesis was not suitable for our statistical learning experiments. In fact, this knowledge attribution was developed in the context of

Artificial Grammar Learning (Andy, Mealor & Dienes, 2013), in which participants may or may not acquire knowledge of the grammar rules. We saw the "rules" attribution as not applicable to the statistical learning paradigms, based on transition probabilities, used in our research. Similarly to our experiments in Chapter 2, standardised verbal instructions (Appendix C) were provided in addition to on-screen instructions. The tasks administered during the test phase were self-paced, in that there was no time limit for response. Overall, the test phase lasted approximately 20 minutes.

3.2.2 Results

Differences between L1 and L2 and triplet preference analysis

To assess whether there were any differences in performance between the L1 and L2 groups, an independent-samples t-test between the proportion of correct responses in the L1 and L2 group was carried out separately for inclusion and exclusion conditions. Under inclusion, the proportion of correct responses in the L2 group ($M = 0.83$ $SD = 0.12$) was significantly higher than in the L1 group ($M = 0.59$ $SD = 0.16$), $t(33) = -4.951$, $p < .001$, two-tailed, 95% CIs of the difference [-0.337 -0.141] Cohen's $d = 0.837$. The same was true under exclusion, we found a significantly higher proportion of correct responses in the L2 group ($M = 0.78$ $SD = 0.12$) than in the L1 group ($M = 0.65$ $SD = 0.13$), $t(33) = -3.207$, $p = .003$, two-tailed, 95% CIs of the difference [-0.222 -0.049] (Figure 3.2).

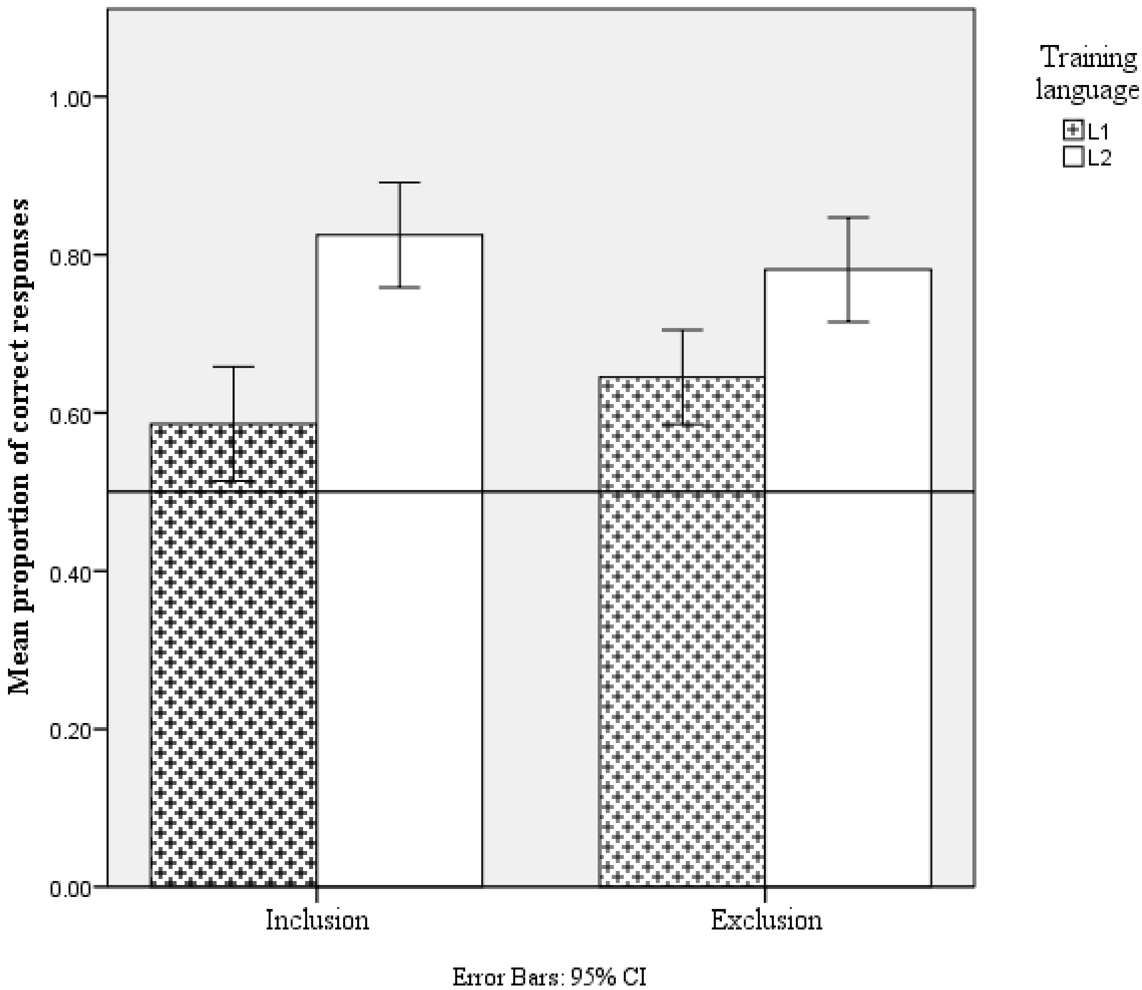

Figure 3.2: Proportion of correct responses for participants trained on L1 and L2, separately for inclusion and exclusion conditions. Line represents chance level (0.5).

As evident from Figure 3.3, triplets from L1 were, overall, chosen more often than triplets from L1. The most popular triplet was Triplet 3 in L2 and the least popular was Triplet 4 in L1. We also carried out two one-way repeated-measures ANOVAs on the number of times that each of the four triplets was chosen separately for L1 and for L2. There was no significant difference in choices between triplets in L1, $F(2.267, 72.550) = 2.626, p = .072, \eta_p^2 = 0.076$ (Greenhouse-Geisser corrected), but there was a significant effect of triplet type in our ANOVA on L2,

$F(3,96) = 3.214, p = .026, \eta_p^2 = 0.091$. Pairwise comparisons showed that this effect was driven by significantly more choices for Triplet 3 than Triplet 1 ($p = .034$).

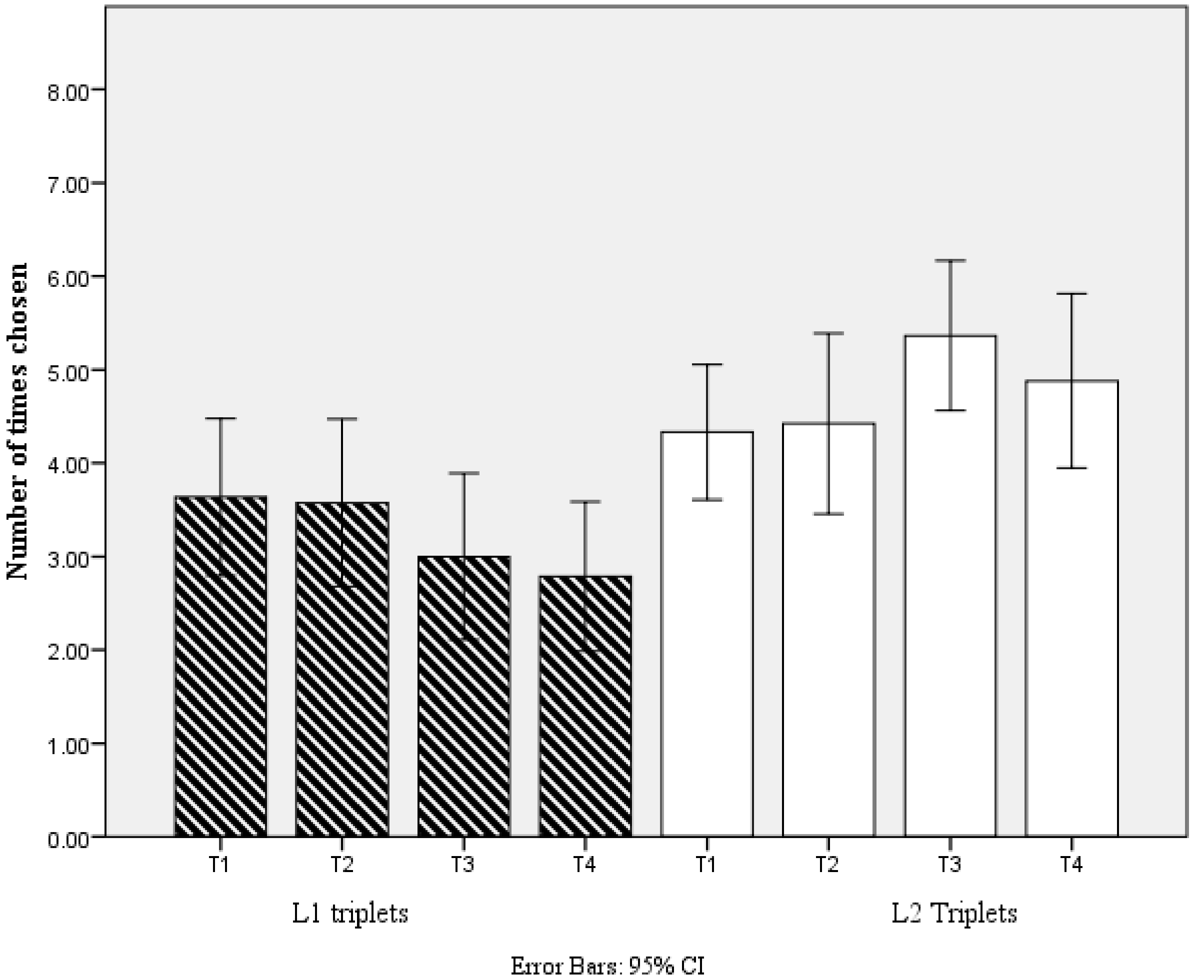

Figure 3.3: average number of times each of the triplets in L1 and L2 were chosen under inclusion. Note: the maximum number of times each individual triplet could be chosen was eight, as each triplet was repeated eight times within the test phase.

This difference in performance between the two training languages led to separate analyses of implicit and explicit knowledge for the two groups.

Process Dissociation Procedure (PDP)

For the purpose of the PDP, the proportion of training triplets chosen was compared to chance level (0.5) separately for inclusion and exclusion instructions. For participants in the L1 group, the proportion of training triplets was significantly above chance under inclusion instructions $t(19) = 2.479$, $p = .001$, one-tailed, 95% CIs of the difference [0.001 0.171], Cohen's $d = 0.554$, and significantly below chance under exclusion instructions, $t(19) = -5.094$, $p < .001$, two-tailed, 95% CIs of the difference [-0.230 -0.061], Cohen's $d = 1.139$, indicating that they had conscious control over their knowledge. This was reinforced by the fact that significantly more training triplets were chosen under inclusion ($M = 0.59$ $SD = 0.15$) than under exclusion ($M = 0.35$ $SD = 0.13$), $t(19) = 4.184$, $p = .001$, two-tailed, 95% CIs of the difference [0.115 0.347], Cohen's $d = 0.936$.

Results were similar for participants in the L2 group. Performance was above chance under inclusion instructions $t(14) = 10.461$, $p < .001$, one-tailed, 95% CIs of the difference [0.245 0.404], Cohen's $d = 2.701$, and participants managed to conform to exclusion instructions by choosing below-chance training triplets under exclusion instructions, $t(14) = -9.131$, $p < .001$, two-tailed, 95%CIs of the difference [-0.372 -0.190], Cohen's $d = 2.358$. Significantly more training triplets were chosen under inclusion ($M = 0.82$ $SD = 0.12$) than under exclusion ($M = 0.22$ $SD = 0.12$), $t(14) = 11.906$, $p < .001$, two-tailed, 95% CIs of the difference [0.497 0.715], Cohen's $d = 3.437$.

See Figures 3.4 and 3.5 for an illustration of the PDP for the L1 and L2 groups.

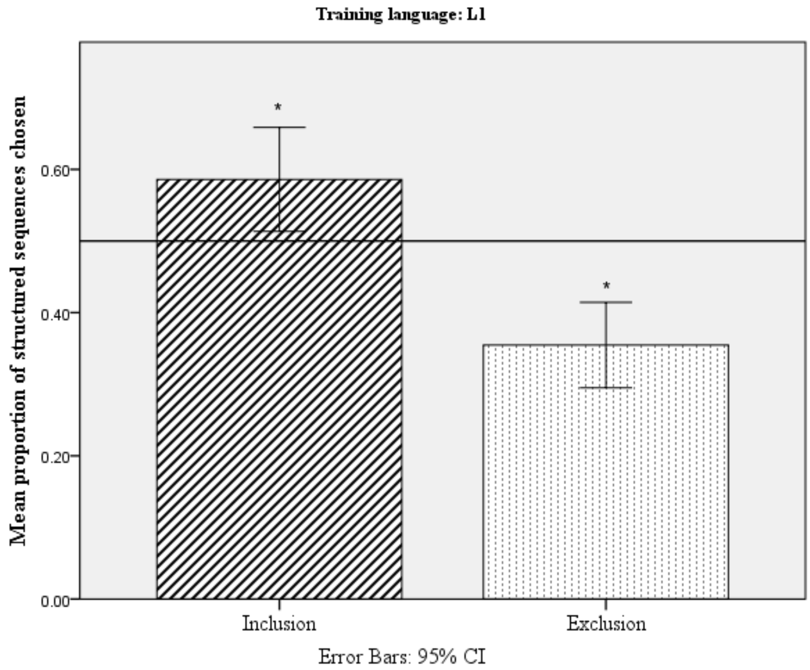

Figure 3.4: Mean proportion of structured sequences chosen under inclusion and exclusion for participants trained on L1. Line represents chance level (0.5). Conditions in which performance significantly differed from chance are marked with one asterisk (*).

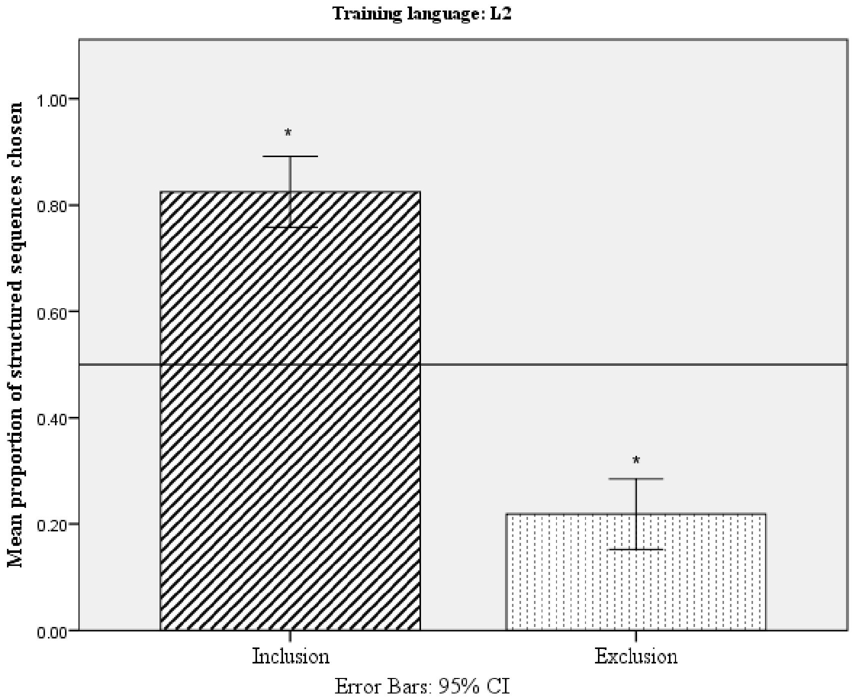

Figure 3.5: Proportion of structured sequences chosen under inclusion and exclusion for participants trained on L2. Line represents chance level (0.5). Conditions in which performance significantly differed from chance are marked with one asterisk (*).

The guessing and zero correlation criteria

The guessing criterion was used to further determine the level of participants' conscious knowledge of the training triplets. This compared the proportion of correct responses in trials in which participants were guessing, using their intuition or their memory to chance level (0.5). This was applied to both inclusion and exclusion. Results indicated that explicit knowledge was present in both the L1 and L2 groups. In fact, knowledge was at chance when participants claimed that they were guessing and significantly above chance when they claimed that they were using their memory. See Table 3.1 for a summary of the guessing criterion.

			N	Mean (*SD*)	*t*	df	*p*	Cohen's *d*
L1	**Inclusion**	**Guess**	16	0.49 (0.29)	-0.116	15	.455	-0.029
		Memory	20	0.62 (0.21)	2.522	19	.010**	0.564
		Intuition	17	0.65 (0.25)	2.557	16	.011**	0.620
	Exclusion	**Guess**	16	0.56 (0.22)	1.071	15	.031**	0.268
		Memory	19	0.65 (0.26)	2.695	18	.015**	0.618
		Intuition	16	0.66 (0.17)	3.937	15	.001**	0.984
L2	**Inclusion**	**Guess**	15	0.53 (0.34)	0.367	14	.360	0.095
		Memory	15	0.88 (0.19)	7.582	14	>.001**	1.958
		Intuition	15	0.62 (0.41)	1.074	14	.150	0.277
	Exclusion	**Guess**	13	0.53 (0.29)	0.363	12	.732	0.101
		Memory	14	0.92 (0.09)	17.638	13	>.001**	4.714
		Intuition	11	0.67 (0.26)	2.215	10	.051	0.668

Table 3.1: One-sample t-tests comparing the proportion of correct responses for each of the three knowledge attributions to chance level (0.5). Results are displayed separately for inclusion and exclusion conditions and for training language. Significant p-values are marked with one asterisk (*) for significance at the 0.05 level and two asterisks (**) for significance at the 0.01 level. Inclusion results are one-tailed.

For the purpose of the zero correlation criterion, we compared participants' confidence between trials in which they were correct and trials in which they were incorrect. We did this separately for inclusion and exclusion and for L1 and L2 participants. Results (Table 3.2) showed that there was no significant difference between confidence when correct and when wrong for participants in L1, but participants in L2 were able to track their knowledge, with significantly higher confidence in correct than incorrect trials.

			N	**Mean (*SD*)**	***t***	**df**	***p***	**Cohen's *d***	**95% Cis of the difference**
L1	**Inclusion**	**Correct**	19	72.20 (7.66)	1.425	18	.171	0.327	[-0.974 5.082]
		Incorrect	19	70.15 (9.73)					
	Exclusion	**Correct**	19	69.07 (8.61)	1.779	18	.092	0.408	[-0.421 5.067]
		Incorrect	19	66.75 (8.45)					
L2	**Inclusion**	**Correct**	14	80.90 (11.95)	4.181	13	.001**	1.117	[4.875 15.300]
		Incorrect	14	70.81 (11.70)					
	Exclusion	**Correct**	15	79.03 (11.91)	4.465	14	.001**	1.153	[6.598 18.795]
		Incorrect	15	66.33 (11.04)					

Table 3.2: Results of paired-samples t-tests comparing confidence in trials when participants were correct and when they were incorrect. Results are displayed separately for inclusion and exclusion conditions and for training language. Significant p-values are marked with one asterisk (*) for significance at the 0.05 level and two asterisks (**) for significance at the 0.01 level.

Overall, explicit knowledge was present in both L1 and L2 groups, but participants in the L2 group seemed to have more explicit knowledge and, overall, higher confidence than participants in the L1 group.

A short pilot experiment using the Bohlen-Pierce scale

We interpreted our findings of a bias towards specific triplets, and of overall better performance within the L2 than L1 group as potentially coming from an effect of lifelong exposure to Western tonal music in our participants. In order to remove these biases, we piloted three participants on an identical version of our experiment which used tones from the Bohlen-Pierce scale instead. The average proportion of correct responses was 0.39 ($SD = 0.07$). We considered this to be too close to chance level (0.5) and an indication that these auditory triplets were too difficult to remember for participants, and therefore did not pursue this pilot experiment any further.

3.2.3 Discussion

This experiment was a part replication of Saffran et al.'s 1999 auditory triplet learning experiment using tone stimuli. In line with these authors, we found that participants acquired knowledge of the tone triplets, as shown by their above-chance discrimination of trained triplets from foil triplets in the 2AFC task. To the best of our knowledge, we do not know of any other auditory triplet learning study using tone stimuli which has assessed implicit and explicit knowledge. The PDP showed that participants were able to control the expression of their knowledge by refraining from choosing training triplets when instructed to do so under exclusion. This was in agreement with the results of the guessing criterion, showing at-chance performance when guessing, and of the zero correlation criterion, which showed significantly higher confidence in correct than incorrect trials.

These findings of entirely explicit knowledge are consistent with the auditory statistical learning results that we obtained in Chapter 2 of this thesis. Although our results are novel, they confirm what was previously found in an auditory triplet learning study which used artificial speech (Franco et al., 2011a) that the knowledge acquired by participants is available to conscious control. Our findings also contribute to the growing evidence accumulated in more recent years within visual triplet learning which suggests that participants develop explicit knowledge of the learned triplets (Bertels et al., 2012b; Bertels et al., 2015a).

Our comparisons between performance in the L1 and L2 groups showed that participants in the L2 group performed significantly better, under both inclusion and exclusion. In fact, preference for individual triplets in L2 was higher than for triplets in L1. We argue that this imbalance in triplet preferences between the two languages poses a problem for auditory triplet learning tasks using tone stimuli, and this is a point that deserves further discussion.

There is evidence from unpublished work (Knast, Durrant, Miranda, & Denham, 2008) for the existence of *a priori* biases towards specific tone triplets in the Saffran task, and for the influence of tonal enculturation, that is, enculturation to Western tonal music, on such biases. Music enculturation can be defined as the development of music schemata as a result of exposure to music within one's own culture (Morrison, Demorest, & Stambaugh, 2008). In their unpublished work, Knast, Durrant, Miranda, & Denham (2008) replicated Saffran et al's 1999 task, but added a forced-choice task prior to the exposure phase, which aimed to detect any *a priori* preferences towards specific tone triplets. They found that participants tended to choose triplets from L2 more frequently than triplets from L1, in line with results of the present experiment. The authors attributed this effect to tonal enculturation, a proposal supported by the finding that exposing an Artificial Neural Network (ANN) to tonal stimuli from Mozart produced similar results, in terms of triplet preference effects, to exposure with the auditory triplets. In fact, the triplets which were most liked were also the ones most frequently occurring in Western tonal music. In this work, the authors also successfully reduced this prior exposure effect, and, conversely, increased the learning effect, by creating tone stimuli which used the Bohlen-Pierce scale instead of the more familiar Western tonal scale. In the small pilot experiment which we conducted using the Bohlen-Pierce scale we found that this was too difficult for participants, and we were not able to observe a learning effect, which led us to abandoning these stimuli.

Based on this evidence that lifelong exposure to Western tonal music leads participants to have a propensity to choose tone triplets which sound more familiar to them, therefore interfering with auditory statistical learning, we suggest that the performance difference observed between the L1 and L2 groups in the present experiment is likely to be due to *a priori* preferences for certain tone triplets dictated by tonal enculturation. In their experiment, Saffran et al., (1999) emphasised that the tones within their triplets had been arranged in a way that avoided the reproduction of familiar musical structure and, furthermore, that they had not been constructed in accordance with any standard rules of music composition. In this experiment we showed that, despite these precautions, participants still show a preference for certain tone intervals. Although participants in the L2 group in Saffran et al.'s (1999) experiment performed better than those in the L1 group, the authors found no significant difference in performance between the two groups. In their work, they did not include a triplet preference analysis, therefore we have no information as to which tone triplets were preferred specifically. This would have been useful in this respect.

In conclusion, our findings raised concerns around the influence of tonal enculturation in auditory triplet learning paradigms which use tone stimuli, and led us to the decision to retain the transition matrix paradigm for the study of statistical learning in the auditory modality. We suggest that, when tested on transition matrix stimuli, participants are less biased by the resemblance of individual intervals to Western tonal intervals, and therefore any learning effect due to the extraction of statistical regularities from the input stimuli is assessed more genuinely.

Overall, in terms of explicit and implicit knowledge, the results of this experiment were in line with the results of our transition matrix experiment on auditory statistical learning. All our measures of conscious knowledge indicated that the knowledge acquired by our participants was fully explicit. This further corroborated the results obtained so far, suggesting that knowledge in auditory statistical learning is held explicitly.

3.3 Visual triplet learning

3.3.1 Materials and methods

3.3.1.1 Participants

Thirty participants took part in the experiment. Participants were a mixture of undergraduate and postgraduate students at the University of Lincoln, or members of the public. Whilst undergraduate students took part in the experiment in exchange for research credit points, the other participants received a cash compensation worked out on the basis of £10 hourly rate for research participants. Fifteen participants were randomly allocated to the Language 1 group, and 15 participants were allocated to the Language 2 group. Demographic information was missing for four participants. Of the participants for which full demographic information was present, six were males (age range = 20-56 years, mean age = 31.83, *SD* = 14.44) and twenty were females (age range = 18-55 years, mean age = 25.00, *SD* = 9.52). Two participants had a diagnosis of dyslexia. All participants had normal or corrected to normal vision and no medical conditions which could have affected their participation or the validity of the data. Twenty-three participants spoke English as their first language and three participants spoke English as their second language.

3.3.1.2 Ethics

The study received ethical approval from the University of Lincoln Psychology Research Ethics Committee (see Appendix A for ethical approval form and full details of ethical approval). Participants provided full informed consent and were free to withdraw from the study at any point without providing any motivation, or to withdraw their data at a later point. At the end of the experiment participants were fully debriefed, verbally and in writing (See Appendix D.2 for participant information sheet, consent form and written debrief form).

3.3.1.3 Stimuli

Our visual triplet learning stimuli followed the same principles as those of our auditory triplet learning experiment, with the exception that visual shapes were used instead of auditory tones. Along the lines of our first visual pilot experiment conducted in Chapter 2 of this thesis, we selected twelve shapes from Fiser & Aslin (2002a). These shapes have been successfully used in several visual triplet learning studies (Fiser & Aslin, 2001; Turk-Browne et al., 2005; Turk-Browne & Scholl, 2009), therefore we deemed them appropriate for our part-replication of this past work.

For the purpose of the two-language design, we grouped to form two sets of four unique triplets, one set for L1 and the other for L2. The triplets for our L1 were identical to the triplets used by Fiser & Aslin (2002a). The authors did not use a two-language design but, instead, for their foil triplets in the 2AFC task they created "impossible" triplets, which were generated by using three successive shapes which had never occurred in succession during exposure. We used the same principle to form our L2 triplets, which used the same 12 shapes to form triplets distinct from the L1 triplets. An illustration of the triplets contained in L1 and L2 can be found in Figure 3.6.

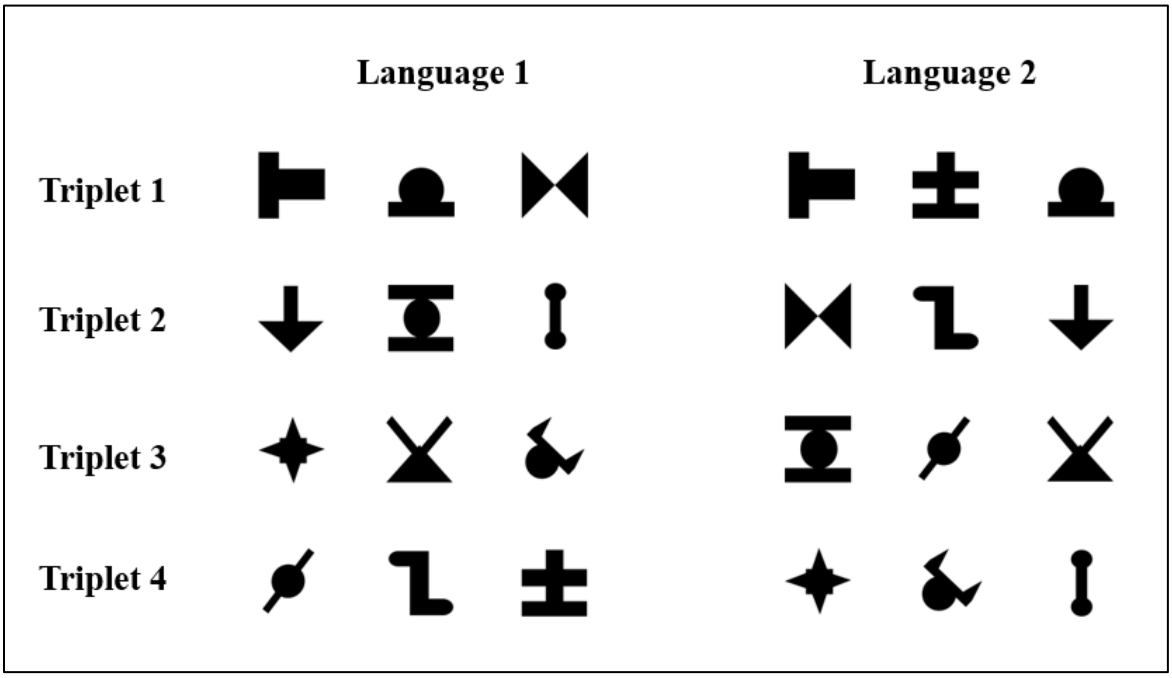

Figure 3.6: Our four shape triplets for Language 1 and Language 2. The two languages were formed by rearranging the twelve unique shapes into two different sets of shape triplets.

3.3.1.4 Apparatus

The experiment was programmed and run using MATLAB R2017a, and the MATLAB Psychtoolbox (Brainard, 1997; Pelli, 1997; Kleiner et al, 2007). The experiment took place in one of the testing cubicles at the University of Lincoln on an HP computer with an Intel ® Core ™ i5 vPro processor. The experiment display and visual stimuli were presented on an HP 24-inch monitor with a resolution of 1920x1080. Participant responses were collected through a Dell keyboard.

3.3.1.5 Procedure

3.3.1.5.1 Exposure phase

We aimed to make our visual and auditory experiments as comparable as possible, therefore the parameters of the symbolic exposure stream were the same between the two. The exposure stream contained 288 shapes in total, that is, 96 triplets. Each of the four triplets appeared 24 times during exposure. Half of our participants were trained on the L1 exposure stream, developed using the L1 triplets and the other half were trained on the L2 exposure stream, developed from the same symbolic exposure stream but using the L2 triplets. The shapes were presented sequentially on the screen. Presentation times were decided on the basis of previous similar research (Turk-Browne et al., 2005). Each shape was displayed on the screen for a duration of 400 msec with an Inter Trial Interval (ITI) of 200 msec, adding up to a total duration of nearly 3 minutes.

Shapes were presented on a white background and, similar to our visual experiment with these shapes in Chapter 2, were enclosed within an imaginary square measuring 1.5 cm x 1.5 cm, in order to achieve uniformity in their size. Participants were seated at a distance of approximately 50 cm from the computer screen. The instructions were equivalent to the auditory experiment: "You will see a series of shapes. Please watch attentively. Press a key to see the shapes". No mention was made of the statistical regularities in the exposure stream or that there would be a test phase afterwards.

3.3.1.5.2 Test phase

The test phase, administered immediately after exposure, was identical to that of the auditory experiment in terms of the trial structure, the implementation of the two-language design, the PDP and guessing and zero correlation criteria. Each of the 32 2AFC test trials consisted of two triplets: one from L1 and the other from L2. All possible combinations of triplets from each of the two languages appeared in the 32 2AFC test trials. The order of presentation of the L1 and L2 triplet within each trial was counter-balanced. There were 8 repetitions of each of the four triplets from L1 and from L2 in the 32 test trials. The order of test trials was randomised per participant. On each 2AFC trial, the two visual shape triplets were presented sequentially, shape by shape, at the same pace as during exposure and each triplet was preceded by the labels "sequence 1" and "sequence 2" on screen for 500 msec before the first and second visual triplet, respectively. Each of the visual triplets, in total, had a duration of nearly 2 seconds. The end of the first test triplet and the presentation of the "sequence 2" label were separated by a 500-msec pause. Trials were separated by a 1-second pause.

Our PDP instructions were equivalent to those of the auditory experiment: "choose which of the two sequences looks more familiar" for inclusion and "choose which of the two sequences looks less familiar" for exclusion. Half the participants were presented with inclusion instructions first and the other half was presented with exclusion instructions first. Responses for the 2AFC were made in the same way as for the auditory experiment by pressing the "1" or "2" keys on the computer keyboard. Confidence and knowledge attribution ratings were also collected in the same way as the auditory experiment for each 2AFC trial. All tasks were self-paced. Overall, the test phase took approximately 20 minutes.

3.3.2 Results

Differences between L1 and L2

In order to assess any differences in performance between the L1 and L2 groups, we carried out an independent-samples t-test between the proportion of correct responses under inclusion and exclusion in L1 and L2. Although the proportion of correct responses under inclusion was higher for the L2 group (M = 0.66 SD = 0.17) than the L1 group (M = 0.61 SD = 0.12), this difference was not statistically significant, t(28) = -1.004, p = .324, two-tailed, 95% CIs of the difference [-0.165 0.056], Cohen's d = -0.183. We obtained similar results for the exclusion condition, with better performance in the L2 group (M = 0.68 SD = 0.15) than the L1 group (M = 0.59 SD = 0.09), but no statistically significant difference, t(28) = -1.862, p = .073, two-tailed, 95% CIs of the difference [-0.179 0.008], Cohen's d = 0.460. As the differences observed between L1 and L2 performance were not significant, data for the two groups were pooled for the purpose of subsequent analyses.

Process Dissociation Procedure

The proportion of training triplets chosen was compared to chance level (0.5) separately under inclusion and exclusion instructions for the purpose of the PDP. Participants were able to demonstrate above-chance knowledge under inclusion instructions $t(29) = 5.019$, $p < .001$, one-tailed, 95% CIs [0.064 0.206], Cohen's $d = 0.916$, and were to withhold their responses under exclusion instructions $t(29) = -5.624$, $p < .001$, one-tailed, 95% CIs [-0.183 -0.085], Cohen's $d = 1.072$, indicating that they had conscious control over their knowledge.

This finding was further reinforced by the fact that the number of training triplets chosen was greater under inclusion ($M = 0.64$ $SD = 0.15$) than exclusion ($M = 0.37$ $SD = 0.13$), $t(29) = 5.919$, $p < .001$, two-tailed, 95% CIs of the difference [0.176 0.363], Cohen's $d = 1.081$. See Figure 3.7 for an illustration of the PDP.

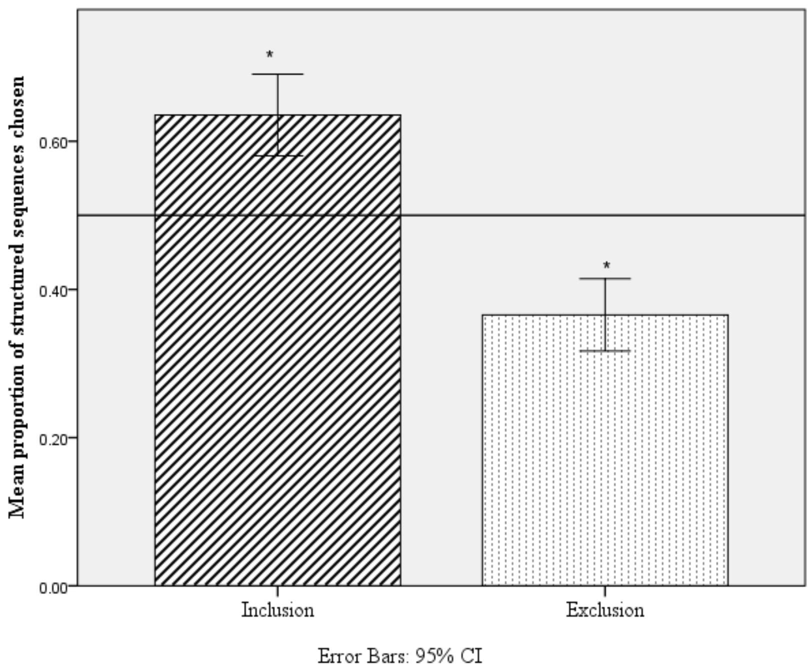

Figure 3.7: Proportion of structured sequences chosen under inclusion and exclusion. Line represents chance level (0.5). Conditions in which performance significantly differed from chance are marked with one asterisk (*).

Guessing and zero correlation criteria

To further determine the level of participants' conscious knowledge of the training triplets, we applied the guessing criterion. For this purpose, we compared the proportion of correct responses in trials in which participants were guessing, using their intuition, or their memory to chance level (0.5). We applied the guessing criterion to both the inclusion and exclusion conditions. Under inclusion, participants performed at chance when they claimed that they were guessing, but significantly above chance when they were using their intuition or their memory (Table 3.3). By the guessing criterion this indicated that they were aware of their knowledge. We obtained similar results under exclusion, with at-chance performance in trials in which participants were guessing and above-chance performance when they were using their intuition and memory, which also indicated explicit knowledge (Table 3.3). See Figure 3.8 and Figure 3.9 for a representation of the guessing criterion under inclusion and exclusion.

		N	**Mean (*SD*)**	***t***	**df**	***p***	**Cohen's *d***
Inclusion	**Guess**	26	0.527 (0.251)	0.544	25	.591	0.107
	Memory	30	0.722 (0.250)	4.868	29	>.001**	0.889
	Intuition	24	0.664 (0.173)	4.674	23	>.001**	0.954
Exclusion	**Guess**	26	0.546 (0.211)	1.112	25	.277	0.218
	Memory	27	0.705 (0.192)	5.561	26	>.001**	1.070
	Intuition	26	0.593 (0.208)	2.294	25	.030**	0.450

Table 3.3: One-sample t-tests comparing the proportion of correct responses for each of the three knowledge attributions to chance level (0.5). Results are displayed separately for inclusion and exclusion conditions. Significant p-values are marked with one asterisk (*) for significance at the 0.05 level and two asterisks (**) for significance at the 0.01 level.

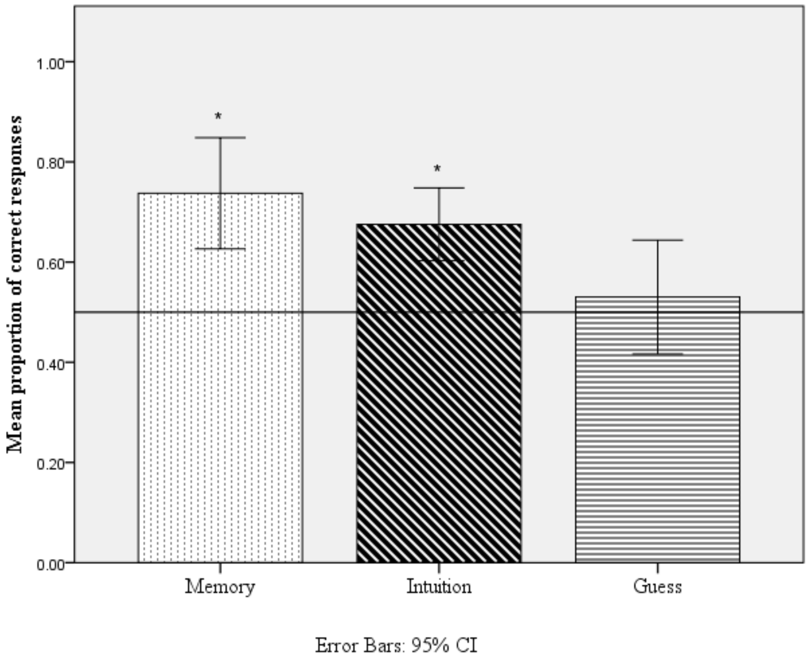

Figure 3.8: Mean proportion of correct responses separately for each type of knowledge attribution under inclusion (guessing criterion). Line represents chance level (0.5). Conditions in which performance significantly differed from chance are marked with one asterisk (*).

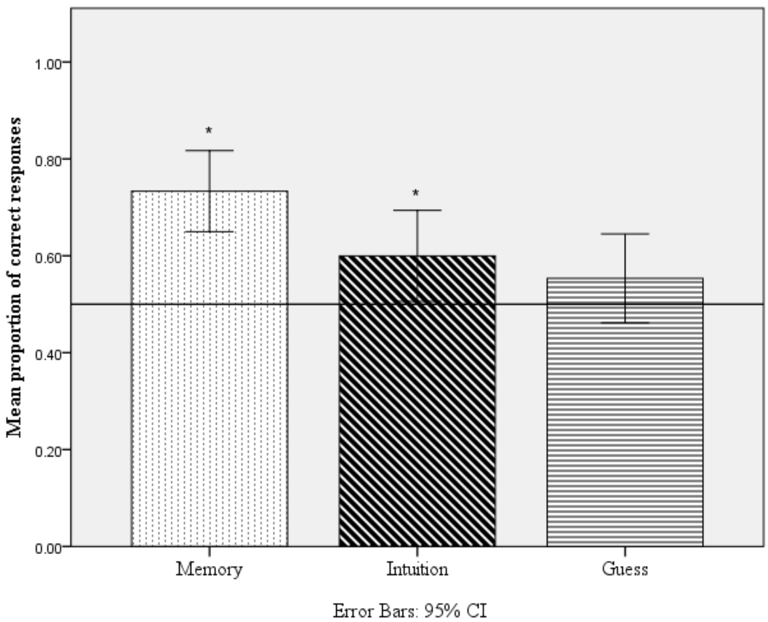

Figure 3.9: Mean proportion of correct responses separately for each type of knowledge attribution (guessing criterion) under exclusion. Line represents chance level (0.5). Conditions in which performance significantly differed from chance are marked with one asterisk (*).

For the purpose of the zero correlation criterion, confidence ratings for correct and incorrect responses were compared. We found significantly higher confidence ratings in correct (M = 71.08 SD = 9.46) than incorrect (M = 65.81 SD = 7.94) trials under inclusion, $t(29) = 3.352$, $p = .002$, two-tailed, 95% CIs of the difference [2.057 8.496], Cohen's d = 0.612. Similarly, under exclusion, confidence ratings were higher for correct (M = 71.27 SD = 7.5) than incorrect (M = 65.38 SD = 8.14) trials, $t(28) = 4.016$, $p < .001$, two-tailed, 95% CIs of the difference [2.887 8.899], Cohen's d = 0.733. Based on the zero correlation criterion, these results indicated that participants were able to track their knowledge.

Triplet preference analysis

To assess whether any biases towards certain shape triplets were present, we carried out two one-way repeated-measures ANOVA on the number of times each triplet was chosen separately for L1 and L2. This analysis was carried out using pooled data from the L1 and L2 groups. Only inclusion data was considered.

Our ANOVA on L1 choices found a significant effect of triplet type, $F(2.302, 62.149) = 7.233$, $p = .001$, $\eta_p^2 = 0.211$ (Greenhouse-Geisser corrected). Pairwise comparisons showed that this was driven by a significant difference between Triplet 3 and Triplet 2 ($p = .045$) and Triplet 3 and Triplet 4 ($p < .001$). No significant effect of triplet type was found in our ANOVA on L2 choices, $F(3, 81) = 1.585$, $p = .199$, $\eta_p^2 = 0.055$ (Figure 3.10).

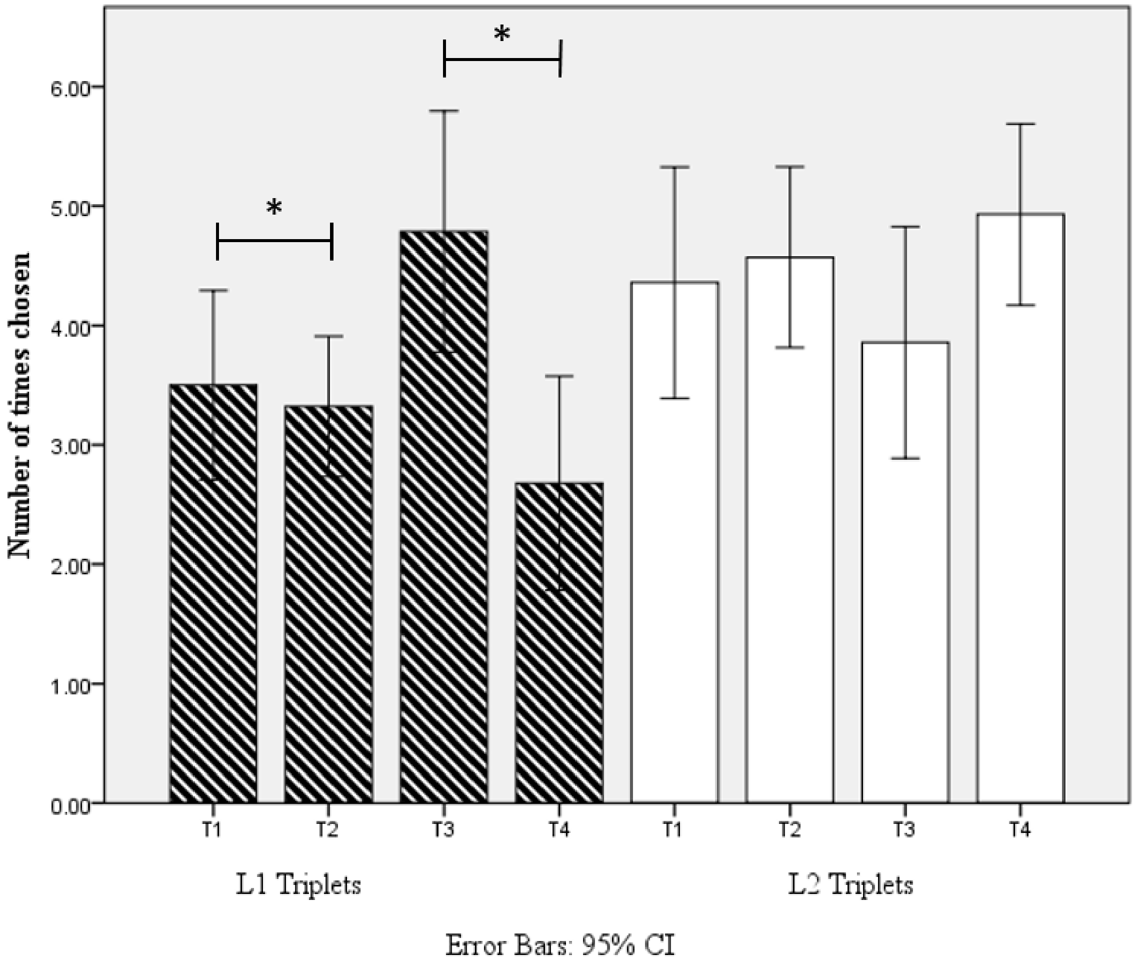

Figure 3.10: Average number of times each of the triplets in L1 and L2 were chosen under inclusion. Note: the maximum number of times each individual triplet could be chosen was eight, as each triplet was repeated eight times within the test phase. Pairs of triplets which differed significantly according to pairwise comparisons are marked with an asterisk (*).

3.3.3 Discussion

In this experiment we aimed to establish a suitable paradigm for the study of implicit and explicit knowledge in visual statistical learning. For this purpose, we adapted a well-known visual triplet learning paradigm for use with the PDP and the guessing/ zero correlation criteria. In line with previous research on visual triplet learning (Bertels et al., 2012b; Bertels et al., 2015a; Fiser & Aslin, 2002a; Fiser & Aslin, 2001; Turk-Browne et al., 2005; Turk-Browne & Scholl, 2009; Turk-Browne et al., 2009; Schapiro et al., 2014), we found that participants successfully learned the triplets through a short exposure phase. Although recent research has used this paradigm in combination with the guessing and zero correlation criteria (Bertels et al., 2012b; Bertels et al., 2015a), to the best of our knowledge, we do not know of any study which has adapted the PDP for use with visual triplet learning in a forced-choice task. This is a novel application of this measure of conscious knowledge which, combined with the use of the guessing and zero correlation criteria, provides useful insight into the status of knowledge in visual statistical learning. Based on the successful application of our methods in this experiment, we decided to retain visual triplet learning as our standard paradigm for the investigation of implicit and explicit knowledge in visual statistical learning.

Through the PDP, our participants were found to have conscious control over their knowledge: they successfully conformed to exclusion instructions by refraining from choosing training triplets in this condition. These results were confirmed by the guessing criterion: participants' performance was indeed at chance in trials in which they claimed that they were guessing, combined with above-chance performance in trials in which they were using memory and intuition. Similarly, participants' confidence was significantly higher in correct than incorrect trials. Both these techniques confirmed that participants were aware of their knowledge. These results were in line with results from our previous experiment on auditory statistical learning using transition matrix (Chapter 2 of this thesis) and our experiment on auditory triplet learning in the present chapter, both of which indicate that the knowledge acquired in statistical learning is explicit. We also provided support for results of previous similar research (Bertels et al., 2012b; Bertels et al., 2015a; Franco et al., 2011a), and added to the weight of recent evidence suggesting that participants acquire conscious awareness of their knowledge in triplet learning.

Our results with regards to participants' preferences for certain shape triplets are something which deserves further consideration. In the present experiment we found that participants trained on L2 had a higher proportion of correct responses in the 2AFC task than participants trained on L1, although this difference was not significant. When looking further into specific triplet preferences, it was evident that, whist choices in the L2 group were more uniformly distributed across the four triplets, participants in L1 were biased towards choosing Triplet 3 in the 2AFC Task, which was chosen significantly more frequently than Triplet 2 and Triplet 4.

In defence of their chosen triplet stimuli, Fiser & Aslin, (2002a) claimed that the distinctiveness of their shapes ensured that these would not be confused with each other. Whilst we took this as a positive characteristic of these stimuli, based on the present findings, we suggest that the opposite could also be true. The fact that the shapes are different from each other could also mean that some shapes might be more memorable or more easily processed due to their distinctive features. In a visual triplet learning experiment, Schapiro et al. (2014) used visual triplets consisting of scene stimuli. These were scenes of natural landscapes presented in colour. It could be that such scene stimuli are less easily verbalisable by participants, and also less distinct in terms of their specific features, making it less likely for participants to develop a preference for one, or more, particular scenes due to their distinctive properties. Based on this, there is a possibility that, if we had used scene stimuli in the present experiment, we would not have observed a triplet preference effect. Within visual triplet learning research, triplets have also been constructed on the basis of glyphs taken from the Sabaean alphabet (Turk-Browne et al., 2009). We argue that these glyphs, being distinct from each other, and varying in complexity, would present the same problem as in the present experiments with regards to whole-triplet or shape preference.

Interestingly, previous studies using visual triplet learning (Bertels et al., 2012b; Bertels et al., 2015a; Fiser & Aslin, 2002a; Fiser & Aslin, 2001; Turk-Browne et al., 2005; Turk-Browne & Scholl, 2009) have not investigated specific-triplet biases, therefore we are the first to remark on this phenomenon. Based on the present results, we cannot firmly conclude whether the observed preference for one specific triplet was due to one specific shape within that triplet, more than one shape, or the way that the shapes were arranged. Answering this question would require a new investigation specifically tailored for this purpose. This would fall outside the scope of our research, which is aimed at investigating implicit and explicit knowledge within statistical learning. Nevertheless, we argue that triplet preference effects within visual triplet learning present a considerable problem for research in this area, as they may interfere with the observation of genuine statistical learning, and that studies should devote some attention to the investigation of the causes of these effects and how to minimise them. In order to remove the imbalance between triplet choices observed within L1 in the present experiment, for the purpose of future experiments we decided to rearrange the triplets in L1 and L2 to form two new shape languages.

With regards to the implementation of the PDP in the context of our forced-choice tasks, in the present chapter, as well as in Chapter 2, we collected participant responses through keys 1, to choose sequence 1, and 2 to choose sequence 2, on the keyboard, which are placed next to each other. However, this setup caused a small number of participants to invert their responses by pressing the opposite key to the one intended. In order to be able to include these participants in the data analysis, upon noticing that their responses had been inverted, we asked them whether they thought they had been pressing the opposite key to the one intended and, if they confirmed this, we inverted their responses for the purpose of data analysis. This limited number of instances is recorded in Appendix F.5. In order to tackle this issue, we decided to change the response keys in subsequent experiments to be at opposite sides of the keyboard (keys “q”, labelled as “1” and “p”, labelled as “2”), and to instruct participants to respond using separate hands instead. We reasoned that this would greatly reduce, or eliminate, the instances of inversions.

So far in this thesis we built a consistent picture that the knowledge acquired in statistical learning is explicit, which is in line with results of recent research. From a methodological point of view, this experiment made an important contribution to the existing literature. Despite the above-mentioned concerns around triplet-specific biases in this paradigm, we successfully established the use of the PDP in the context of a forced-choice task within visual triplet learning as a suitable measure of conscious knowledge. For future studies, we planned to build on these findings, and to adopt this methodology for the study of statistical learning in the visual modality.

3.4 Conclusions

The present study successfully implemented the combined use of the Process Dissociation Procedure (PDP) and the guessing and zero correlation criteria in an auditory and a visual triplet learning paradigms. We found that these measures of conscious knowledge are suitable for use in both the auditory and visual modalities when using this paradigm although, given our concerns regarding the amount of unbiased learning measurable through the auditory triplet learning paradigm, we decided to abandon this for the auditory modality. In the present chapter, all our measures of conscious knowledge indicated that knowledge is fully explicit both in auditory and in visual statistical learning. More specifically, we found that participants are able to control the expression of the knowledge they have acquired, based on the PDP, and that they are aware that they hold this knowledge, based on the guessing and zero correlation criteria.

We also discovered that in both the auditory and visual triplet learning paradigms participant biases towards specific triplets are present. We regard this as an important discovery, which has methodological implications for these paradigms, and, to the best of our knowledge, we are the first to draw attention to these biases. The presence of preferences for certain triplets led us to the decision to discontinue using the auditory triplet learning paradigm. This is because preference effects were larger in the auditory experiment, leading to a significant difference in performance between participants trained on L1 and L2, and because of evidence (Knast, Durrant, Miranda, & Denham, 2008) (unpublished) that these biases may be due to tonal enculturation (Morrison et al., 2008) a phenomenon which we could not guard ourselves against. Within the visual paradigm, we decided to address the issue of triplet preferences in future experiments by rearranging our visual triplets on the basis of the preference findings in the present study.

Overall, in our experiments up to this point, we found no support for the presence of implicit knowledge in statistical learning. This adds to the more recent evidence gathered in this field (Bertels et al., 2012b; Bertels et al., 2015a; Franco et al., 2011a), that explicit knowledge is produced as a result of statistical learning, and runs counter to the original assumption that statistical learning can be considered a form of implicit learning (Pierre Perruchet & Pacton, 2006).

Based on the present study, we decided that our future work on implicit and explicit statistical learning would use the transition matrix paradigm to investigate the auditory modality and the triplet learning paradigm to investigate the visual modality. Given the evidence that we gathered in favour of the role of explicit knowledge in statistical learning, we decided to dedicate our future investigations to the validation and consolidation of these findings.

Chapter 4 Direct and indirect measures of conscious knowledge

4.1 Introduction

In Chapter 2 and Chapter 3 of this thesis we found little evidence for the use of explicit knowledge in visual and auditory statistical learning. Some authors have advocated a different approach to the measurement of implicit and explicit knowledge, which is based on a comparison of direct and indirect tasks. This approach is proposed to be a more sensitive measure of conscious knowledge, and has been prevalent in some of the literature (Reingold & Merikle, 1988). Based on this stream of work, a logical next step was to address the hypothesis that the measures of conscious knowledge that we had used so far have limited sensitivity, and that this is the underlying cause for the little evidence that we found for implicit knowledge. We addressed this hypothesis by using a combination of direct and indirect tasks.

Reingold & Merikle (1988) originally proposed the comparison of direct and indirect tasks as a solution to the shortcomings of recognition and forced-choice tasks. Specifically, their violation of the exhaustiveness assumption, that an explicit measure is able to capture all of the participant's explicit knowledge, and exclusiveness assumptions, that an explicit measure is exclusively sensitive to explicit knowledge (Shanks & St John, 1994). While a direct task explicitly points participants to dimensions of the stimuli which are relevant for learning, the instructions in an indirect task do not make any reference to the relevant knowledge to use (Bertels et al., 2015b). Within this framework, forced-choice tasks have been claimed by some to be "explicit" tasks (Kim et al., 2009). An example of the application of the comparison between direct and indirect measures is the study by Jimenez et al., (1996b), where the authors obtained evidence of unconscious knowledge by comparing performance measured indirectly through response times in a SRTT and directly through a generation task. The underlying logic of this method is that if performance on the indirect task detects any knowledge that is not detected by the direct task, thus producing a performance dissociation between the two measures, knowledge is to be interpreted as implicit (Kim et al., 2009; Bertels et al., 2012a; Bertels, Demoulin, Franco, & Destrebecqz, 2013), in the sense that it not available for use in the direct task. Based on these premises, if in the present study we found no dissociation between direct and indirect measures, this would suggest that all the knowledge acquired by our participants had been correctly detected by our forced-choice task.

In this study, following on from previous authors, we used a Rapid Serial Visual Presentation (RSVP) task as our indirect measure of performance. This task was first applied by Turk-Browne et al., (2005) in the context of a visual triplet learning paradigm using shape stimuli, and more recently used for the purpose of measuring implicit learning in this paradigm by comparing direct and indirect measures of knowledge (Kim et al., 2009; Bertels et al., 2012a; Bertels et al., 2013; Bertels et al., 2015b). In the task, after an exposure phase, participants are presented with a continuous stream of shapes, made by randomly concatenating the triplets that they have been trained on during exposure, and are asked to make a speeded response to a given target shape within the stream. Each trial in the task consists of a different stream of shapes and a different target shape. Learning is evidenced by faster response times to target shapes which are in second and third position within a triplet, therefore predictable, compared to target shapes in first position within a triplet, which are not predictable (Kim et al., 2009; Bertels et al., 2012a; Bertels et al., 2013; Bertels et al., 2015b). The task makes no direct reference to the dimension of the stimuli relevant to the task, hence why it is considered an indirect measure of knowledge (Turk-Browne et al., 2005).

Within a visual triplet learning paradigm, a performance dissociation between the RSVP task and a forced-choice measure of performance is manifested as a difference in response times between shape positions in the RSVP task, concurrently with chance performance in the forced-choice task. The presence of this dissociation has been taken as evidence that the knowledge developed in the task is held implicitly, following the argument that in the direct task, that is, the forced-choice task, participants are required to respond on the basis of their explicit knowledge (Kim et al., 2009). Research which has used this method in a visual triplet learning paradigm has produced inconsistent results, some suggesting that participants' knowledge of the statistical regularities is implicit (Kim et al., 2009), and some suggesting that it is explicit for the most part (Bertels et al., 2012a; Bertels et al., 2013; Bertels et al., 2015b).

This study aimed to investigate the sensitivity of our measures of implicit and explicit knowledge used in Chapter 2 and Chapter 3 of this thesis, by looking for a potential dissociation between forced-choice task performance and performance in an RSVP task. Our goal was to test the hypothesis that combining direct and indirect tasks might reveal useful information about the presence of implicit knowledge, which may have been left undetected in our experiments thus far.

Due to the fact that the RSVP task is to be specifically implemented with a triplet structure, and that retaining a target sound in memory whilst other sounds are being played seemed to us too difficult a task, we were forced to limit this investigation to the visual modality. Furthermore, adding the RSVP to our visual triplet learning paradigm would considerably lengthen the total experiment duration, thus potentially leading to poor performance by our participants due to fatigue. Given that we are aware of the importance of participants' involvement with the task, in particular with the visual triplet learning paradigm, we decided to drop use of the PDP from this study and, instead, to use the most common administration of the forced-choice task which utilises inclusion instructions only. We believed that we would nevertheless be able to comment on the sensitivity of the PDP by comparing our work in this study with the work reported in Chapter 2 and Chapter 3.

As a way to further evaluate the sensitivity of our measures of conscious knowledge, we introduced a generation task in this study. Shanks & St John, (1994) have proposed that generation tasks are more likely to meet the information criterion, due to the use of similar retrieval conditions to the learning task, and the sensitivity criterion, due to their greater ability to detect conscious knowledge. This is a view that we share, and we hypothesised that a generation task may be able to detect more conscious knowledge than the forced-choice tasks that we had used thus far in our research. We believed that valuable knowledge would be gained in this study through the use of a generation task. Within statistical learning, the generation task has previously been used in SRTT experiments, where it has been useful for the assessment of implicit and explicit knowledge through the PDP (Bischoff-Grethe et al., 2004; Norman & Price, 2010; Fu et al., 2008a; Fu et al., 2013). Despite this, statistical learning research has not made use of this task in the context of visual triplet learning, possibly due to the methodological challenges involved in getting participants to generate shapes. The task that we believed to be the closest to a generation task is a "matching questionnaire" developed by

Kim et al., (2009), in which participants were presented with one shape and were asked to choose from eleven shape alternatives which two shapes they thought were grouped with this. We believed that, through a generation task, insight could be gained not only on implicit and explicit knowledge in visual triplet learning, but also on the functioning of the available measures of conscious knowledge. Therefore, we developed a generation task aimed at assessing participants' explicit recollection in this study. We were particularly interested in comparing the results of this generation task to the results of the forced-choice tests and the RSVP.

Furthermore, in light of the fact that we found little evidence for implicit knowledge in adults thus far in this thesis, we were interested in potential differences in the use of implicit and explicit knowledge between adults and children in visual triplet learning. This curiosity was primarily based on Daltrozzo & Conway's (2014) developmental model of statistical learning, discussed in more detail in Chapter 2 of this thesis, which proposes that statistical learning is composed of two systems: the "basic" system, consisting of more implicit knowledge, which is thought to be more prevalent in children, and the "expert" system, which makes use of more explicit knowledge, and is thought to be more prevalent in adults. Given our findings so far that adults appear to be using primarily explicit knowledge in visual statistical learning, we needed to address the possibility that children, in contrast, may be using more implicit knowledge.

Chapter 2 in this thesis investigated auditory statistical learning in children, and a thorough review of infants' and children's performance in statistical learning tasks, in the visual and auditory modality, is contained there. Therefore, for the purpose of this study, we limited ourselves to briefly reporting evidence relating to visual statistical learning. This ability is found to be present in new-borns (Bulf et al., 2011), as well as and infants (Kirkham et al., 2002; Slone & Johnson, 2018). Although visual triplet learning is present in both children and adults (Arciuli & Simpson, 2011; Arciuli & Simpson, 2012b), it seems to follow a developmental trajectory, improving with age (Vaidya et al., 2007; Arciuli & Simpson, 2012b; Arciuli & Simpson, 2011). With regards to implicit and explicit knowledge in visual statistical learning in children, although some research fits within the developmental model proposed by

(Daltrozzo & Conway, 2014), suggesting that explicit knowledge follows a developmental trajectory (Thomas & Nelson, 2001), other research opposes this, suggesting that both adults and children develop explicit knowledge in statistical learning tasks (Weiermann & Meier, 2012; Bertels et al., 2015b). It has to be noted that these contrasting results might originate from the differences in the statistical learning paradigms used. The studies by Thomas & Nelson, (2001) and Weiermann & Meier, (2012) were motor learning studies which used variants of the SRTT and assessed conscious knowledge through verbal generation tasks. In contrast, Bertels et al., (2015b) investigated visual triplet learning and measured conscious knowledge through the use of the guessing criterion, adjusted for use with children through the use of binary confidence ratings. This study used a very similar methodology to Bertels et al., (2015b), as they successfully employed the comparison of direct and indirect measures of knowledge for study with children.

Following on from Bertels et al., (2015b), we also introduced a four-alternative forced-choice (4AFC) task in our paradigm, which we believed would not only be more suitable for use with children, but would also produce interesting knowledge with regards to comparing its sensitivity to the two-alternative forced-choice task. Aiming to compare the information provided by subjective measures of performance, such as confidence ratings and knowledge attribution ratings, to the forced-choice tasks and the indirect task, for our experiment on adults our paradigm included: a two-alternative forced-choice task, a four-alternative forced-choice task, both combined with confidence and knowledge attribution ratings for the purpose of the guessing and zero correlation criterion, an RSVP task and a generation task. We used a shorter version of the experiment on children which only involved a four-alternative forced-choice tasks combined with knowledge attribution ratings and an RSVP task. We believed that a combination of subjective and objective, as well as direct and indirect, measures would be most informative with regards to the use of implicit and explicit knowledge in visual triplet learning.

Based on previous studies, including our own work in Chapter 3, supporting the ability of both adults and children to learn visual statistical regularities, we expected above-chance learning of the triplet structure, as assessed by the 2AFC and 4AFC tasks, in both age groups. Based on the findings of our previous studies, as well as other existing research (Bertels et al., 2012b;

Bertels et al., 2013; Bertels et al., 2015b), we expected the guessing and zero correlation criteria to detect mostly explicit knowledge in both age groups, although we hypothesised that more implicit knowledge may be present in children, based on the developmental hypothesis of statistical learning put forward by Daltrozzo & Conway, (2014). In terms of our comparison of direct and indirect tasks, when explicit knowledge is present, we expected learning in the forced-choice tasks to also be evident as faster response times to shapes in second and third position, than first position within triplets in the RSVP task, therefore no dissociation between direct and indirect measures. Although we expected any implicit knowledge to manifest itself as evidence of learning in the RSVP, paired with chance learning in the forced-choice tasks, given our expectation of mainly explicit knowledge, we did not anticipate this dissociation to be present in adults, but possibly in children, if they made use of more implicit knowledge.

4.2 Direct and indirect measures in adults – Version 1

4.2.1 Materials and methods

4.2.1.1 Participants

Forty-two participants took part in the experiment. Participants were undergraduate students at the University of Lincoln and took part in the experiment in exchange for research credit points. There were two males (age range = 19-20 years, mean age = 19.5, *SD* = 0.71) and forty females (age range = 18-35 years, mean age = 20.00, *SD* = 2.70). First language and dyslexia data was only available for 28 participants. All of these, except one, spoke English as their first language, and no participants had a diagnosis of dyslexia. All participants had normal or corrected to normal vision and no medical conditions which could have affected their participation or the validity of the data.

4.2.1.2 Ethics

The study received ethical approval from the University of Lincoln Psychology Research Ethics Committee (see Appendix A for ethical approval form and full details of ethical approval). Participants provided full informed consent and were free to withdraw from the study at any point without providing any motivation, or to withdraw their data at a later point. At the end of the experiment participants were fully debriefed, verbally and in writing (See Appendix E.1 for participant information sheet, consent form and written debrief form).

4.2.1.3 Stimuli

The individual shape stimuli were identical to those of our visual triplet learning experiment in Chapter 3 of this thesis. Due to the lack of a significant difference in performance between Language 1 (L1) and Language 2 (L2) in Chapter 3, and for consistency with previous research which used a similar methodology to the present study (Bertels et al., 2015a), the two-language design was not used in this study. Therefore, all participants were trained on triplets from L1, and triplets from L2 constituted the untrained, foil triplets.

Based on our results of biases in favour of certain triplets obtained in Chapter 3, in which participants had shown a clear preference for Triplet 3 in L1, in the present experiment we aimed to achieve a more balanced triplet preference within this language. Therefore, we rearranged the two triplet languages used by replacing Triplet 3 in L1 with Triplet 4 in L2. See Figure 4.1 for the new arrangement of triplets in L1 and L2 and refer to Appendix E.6 for a comparison of the two visual triplet languages used in Chapter 3 and the present chapter.

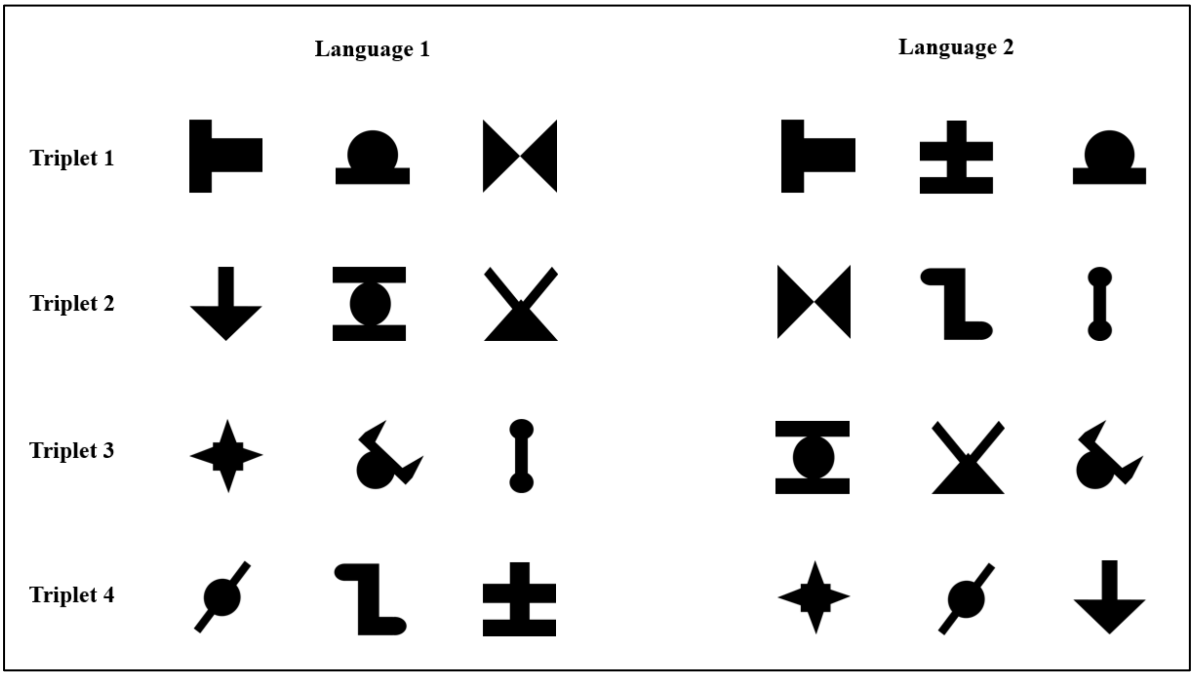

Figure 4.1: New arrangements of shapes forming the visual triplets for Language 1 and Language 2. Training triplets are presented on the left and new/ untrained triplets are presented on the right.

4.2.1.4 Apparatus

Similarly to Chapter 3, the experiment was programmed and run using MATLAB R2017a, and the MATLAB Psychtoolbox (Brainard, 1997; Pelli, 1997; Kleiner et al, 2007). The experiment took place in one of the testing cubicles at the University of Lincoln on an HP computer with an Intel ® Core ™ i5 vPro processor. The experiment display and visual stimuli were presented on an HP 24-inch monitor with a resolution of 1920x1080. Participant responses were collected through a Dell keyboard.

4.2.1.5 Procedure

The exposure phase was followed by a test phase consisting of: 2AFC task, 4AFC task, RSVP task and generation task, administered in this order and with no breaks in-between. The experiment lasted 45 minutes overall.

4.2.1.5.1 Exposure phase

The exposure stream was identical to that of our visual triplet learning experiment in Chapter 3 of this thesis. It consisted of 96 triplets, each appearing 24 times during exposure, which added up to a total of 288 shapes. Based on findings of successful learning in our previous experiment, each shape remained on the screen for a duration of 400 msec, with an ITI of 200 msec.

For consistency with Bertels et al., (2015a), we used a distractor task during exposure, which was irrelevant to learning, and solely aimed at maintaining participants' attention to the exposure stream.

The distractor stimulus was randomly interspersed within the exposure stream and participants were asked to press the space bar as quickly as possible when the distractor appeared on the screen. The distractor was a cartoon character chosen from Bertels et al., (2015a), the Marsupilami. This was presented in colour and enclosed within an imaginary square measuring 3cm x 3cm, twice as much as the imaginary square within which the shape stimuli were enclosed (Figure 4.2).

Figure 4.2: The cartoon character (Marsupilami) used as visual distractor during the exposure phase. Note that this image is not real-size, and that figure boundaries are only present for the purpose of visual presentation in this thesis. No boundaries were used for visual presentation within the experiment.

In keeping with the presentation times of the visual shapes, the distractor was presented on the screen for 400 msec, and the ISI between the distractor and the next visual shape was 200 msec. There were 13 distractors in total within the exposure stream which, together with the 288 exposure shapes, added up to a total of 301 exposure trials. This was similar to Bertels et al., (2015), whose exposure stream contained 5% of distractors. Distractors were positioned randomly throughout the exposure stream for each participant with the constraint that two consecutive distractors were not allowed and that distractors could only appear across triplet boundaries, not within a triplet. This was to avoid disrupting learning of the triplet structure. At least one triplet was presented before the first distractor and after the last, therefore the exposure stream could not begin or end with a distractor.

As in our previous visual statistical learning experiments, the shapes were black and appeared on a white background, and, in order to equate them for size, they were enclosed within an imaginary rectangle measuring 1.5cm x 1.5 cm. The instructions were the same as our previous visual experiment, with the exception that participants were told that, occasionally, a cartoon character would appear, and were instructed to respond to this by pressing the space bar as quickly as possible upon seeing it (see Appendix E.3 for on-screen task instructions). Response times for this cover task were recorded. In total, the exposure phase lasted three minutes.

4.2.1.5.2 Test phase

2AFC

The 2AFC task, as well as the implementation of the guessing and zero correlation criteria, were identical to our visual triplet learning experiment in Chapter 3. However, in order to prevent participant errors due to pressing the wrong response key, response keys were changed to the "q" key on the keyboard to choose the 1st sequence that was presented (this key was labelled "1" using a keyboard sticker) and to the "p" key to choose the second sequence that was presented, labelled "2" using a keyboard sticker. Participants were asked to make their responses with separate hands and to place their left index finger on the "q" key and their right index finger on the "p" key. Furthermore, to prevent participants forgetting the specific inclusion or exclusion instructions, on-screen instructions were used when a response was required to not only remind the participants of the response keys, but also of the specific instructions. These appeared on the screen on three separate lines, to ensure clarity. For inclusion, prompts were: "Respond now", "1 = sequence 1 sounds MORE familiar", "2 = sequence 2 sounds MORE familiar". Prompts for exclusion were the same but the phrase "LESS familiar" was used instead.

4AFC

In the 4AFC task participants were presented, on each trial, with a triplet from which a shape was missing, either in first, second or third position within the triplet. A red question mark was used in place of the missing shape. On each trial, the two given shapes within the triplet, along with the question mark, were first presented sequentially on the screen using the same presentation timings as during exposure, to reproduce the mode of presentation of the exposure phase. Subsequently, the two shapes and question mark were displayed in the upper part of the computer screen. Underneath this display, four shapes were laid out, numbered 1-4, from which participants had to choose by typing a number 1-4 for the corresponding shape (refer to Appendix E.4 for an image of the static visual display). No time limit was given for response.

There were 24 test trials in total, with each triplet presented six times, therefore each missing shape in first, second or third position was presented twice throughout the test. The order of the four shape alternatives was randomised on each trial and presentation of completion trials was randomised per participant. For the purpose of the guessing and zero correlation criteria, after each trial, confidence and knowledge attribution ratings were collected in an identical way to the 2AFC task. The completion task lasted approximately five minutes.

RSVP

In the RSVP task participants were instructed to detect a target shape within a stream of rapidly presented shapes by pressing the space bar as quickly as possible on appearance of the target shape. On each trial, first the label "target" was displayed in the centre of the screen for 500 msec, to focus participants' attention and alert them that the target shape was coming up. After this, the target shape appeared in the centre of the screen and remained there for 1 second, to ensure that participants could process it and prepare to search for this in the upcoming stream of shapes. As soon as the target shape disappeared, the stream of 12 shapes was presented. The shapes appeared sequentially on the screen, in the same way as during exposure. To match the visual presentation in Bertels et al., (2015a), each shape remained on screen for 250 msec with an ISI of 250 msec. Each 12-shape stream was obtained by randomly concatenating the four shape triplets with the constraint that the triplet containing the target had to be either in second or third position within the sequence of four triplets. This was to prevent target shapes from appearing too early or too late within the stream. Each target shape was presented four times, which resulted in 48 test trials. The order of trials was randomised per participant. One practice trial was given before the RSVP task begun to ensure that they had understood what was required in the task. The practice trial used a random sequence of the 12 shapes, not a concatenation of the triplets. The RSVP took approximately eight minutes to complete.

Due to the high level of detail of the on-screen RSVP task instruction, and the fact that these were complemented by a practice trial, the experimenter did not accompany these with standardised verbal instructions. Refer to Appendix E.3 for on-screen task instructions.

Generation task

Before the generation task, participants were verbally debriefed about the triplet structure underlying the shape stimuli. They were then presented with a Power Point slide containing the 12 shapes, arranged in a different random order for each participant at the top of the slide and, underneath this, an empty 4 x 3 table to contain the four triplets. Participants were asked to fill this table by dragging and dropping the 12 shapes to form as many of the four triplets as they could remember. Before participants begun the task, the experimenter made sure that they had understood what was required and the 4 x 3 layout of the table. No time limit was given to complete this task but participants completed this within 2 minutes, on average.

At the end of the experiment, participants were thanked and given a written debrief. Overall, the experiment took approximately 40 minutes to complete. Refer to Appendix C for standardised verbal instructions for all tasks.

4.2.2 Results

Exposure

Exposure data was available for 27 out of the 42 participants who took part in the experiment, as data for 15 participants was lost due to a Matlab technical fault. We established a time window for correct response which went from 150 msec post distractor to 600 msec post distractor. Any response times falling outside of this time window were deemed incorrect. As detailed in subsequent sections of this study, this is a slightly stricter criterion for correct responses than that adopted in our RSVP analysis. This was to ensure that our participants paid complete attention to the exposure stream. We adopted a 60% distractor detection rate as a threshold for discarding participants who were deemed to not have paid enough attention to the exposure stream. Any participant who detected distractors below this threshold was discarded from subsequent analyses. Only one participant was discarded on the basis of this criterion, as he/ she only detected 14% of distractors. The remaining 26 participants for whom exposure data was available, on average, detected 88.74% of distractors (*SD* = 9.93), with an average response time of 338.76 msec (*SD* = 37.59).

2AFC

Having discarded one participant on the basis of their performance in the exposure task, data for 41 participants were analysed. The mean proportion of correct responses in the 2AFC task was 0.55 (*SD* = 0.13) A one-sample t-test revealed that this was significantly above chance (0.5), $t(40) = 2.322$, $p = .013$, one-tailed, 95%CIs [-0.012 0.108], Cohen's $d = 0.36$, suggesting that participants had successfully learned the statistical structure of the stimuli. See Figure 4.3 for a dot plot of participants' performance in the 2AFC task.

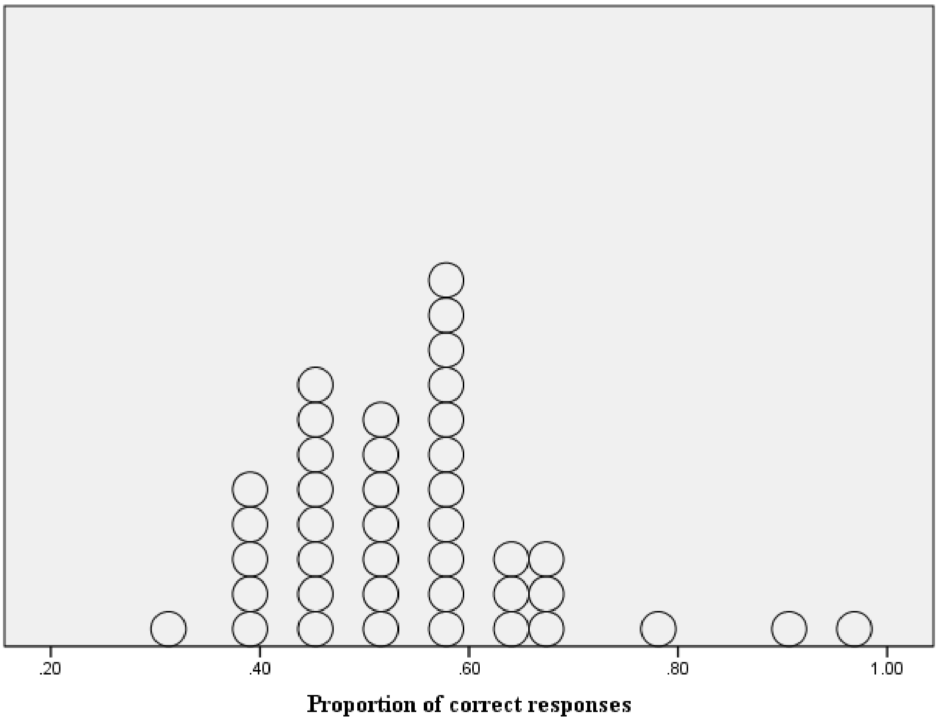

Figure 4.3: Simple dot plot of participants' performance in the 2AFC task, representing each individual's proportion of correct responses.

The mean proportion of guess attributions was 0.39 (*SD* = 0.21), the proportion of intuition attributions was 0.35 (*SD* = 0.17) and the proportion of remember attributions was 0.29 (*SD* = 0.18). A one-way repeated-measures ANOVA on the three types of knowledge attribution showed that there was no significant difference in their use, $F(2, 72) = 1.262$, $p = .289$, $\eta_p^2 = 1.034$.

Performance was at chance when participants were guessing, $t(40) = 1.474$, $p = .074$, one-tailed, 95%CIs [-0.031 0.119], Cohen's $d = 0.23$, and when they were using their intuition, $t(38) = -0.107$, $p = .458$, one-tailed, 95%CIs [-0.082 0.075], Cohen's $d = -0.01$, but above chance when they were remembering, $t(31) = 2.240$, $p = .016$, one-tailed, 95% CIs [-0.001 0.202], Cohen's $d = 0.396$. According to the guessing criterion, this is indicative of explicit knowledge (Figure 4.4). However, there was no significant difference between participants' confidence in trials when they were correct ($M = 63.85$ $SD = 5.74$) and in trials when they were wrong (M = 63.7 SD = 5.72), t (38) = 0.291, p = .772, two-tailed, 95% CIs [-0.917 1.214], Cohen's d = 0.047, which would either suggest the presence of implicit knowledge by the zero correlation criterion, or that the confidence ratings were not sensitive enough to discriminate between participants' confidence in the two conditions.

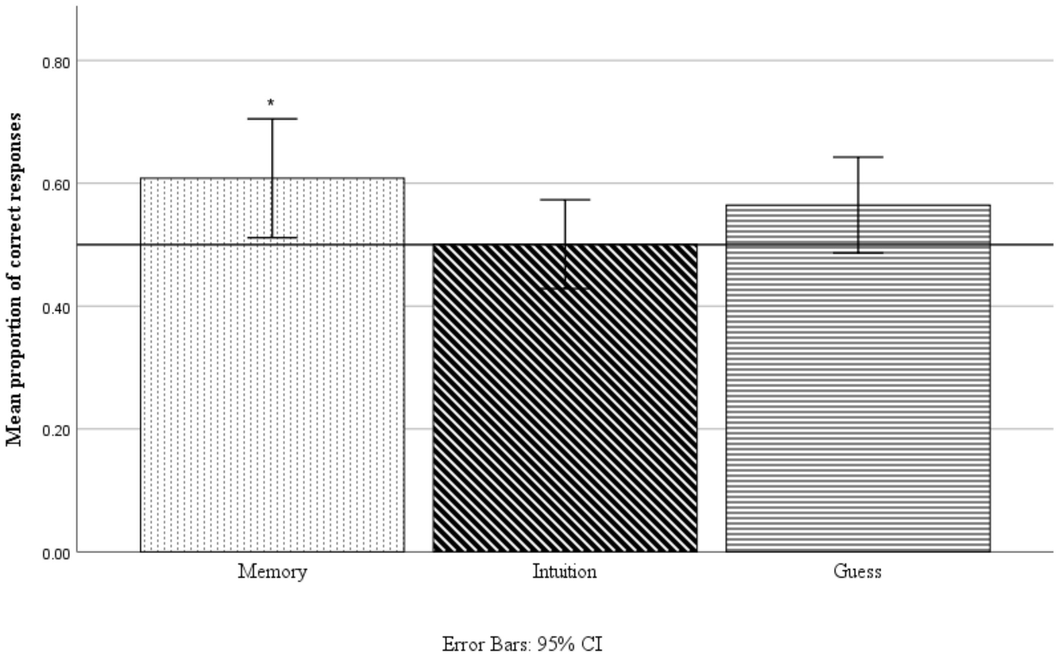

Figure 4.4: Mean proportion of correct responses in the 2AFC task separately for each type of knowledge attribution (guessing criterion) under inclusion instructions. Line represents chance level (0.5). Conditions in which performance was significantly different from chance are marked with one asterisk (*).

A paired-samples t-test between the number of correct responses in the first and second half of the test was carried out to assess the possibility of within-test learning. This was non-significant (p = .634), indicating that participants' performance did not improve during the course of the test.

In order to assess whether participants' choices were biased towards specific shape triplets, a one-way repeated-measures ANOVA was carried out on the number of times each of the four triplets, in L1 (the training language) and L2 (the untrained language) was chosen, regardless of correctness. There was no significant effect of triplet type for L1 triplets, $F(3, 120) = .854$, $p = .467$, $\eta_p^2 = 0.021$ or for L2 triplets, $F(3, 120) = 2.237$, $p = .087$, $\eta_p^2 = 0.053$, indicating that participants were not biased towards choosing a specific triplet irrespective of correctness.

4AFC

The mean proportion of correct responses in the 4AFC task was 0.37 ($SD = 0.16$), and this was significantly above chance (0.25), $t(40) = 4.592$, $p < .001$, one-tailed, 95% CIs [0.049 0.185], Cohen's $d = 0.717$, suggesting that participants were able to successfully use their knowledge of the triplet structure in this task. For a dot plot of performance in the task see Figure 4.5.

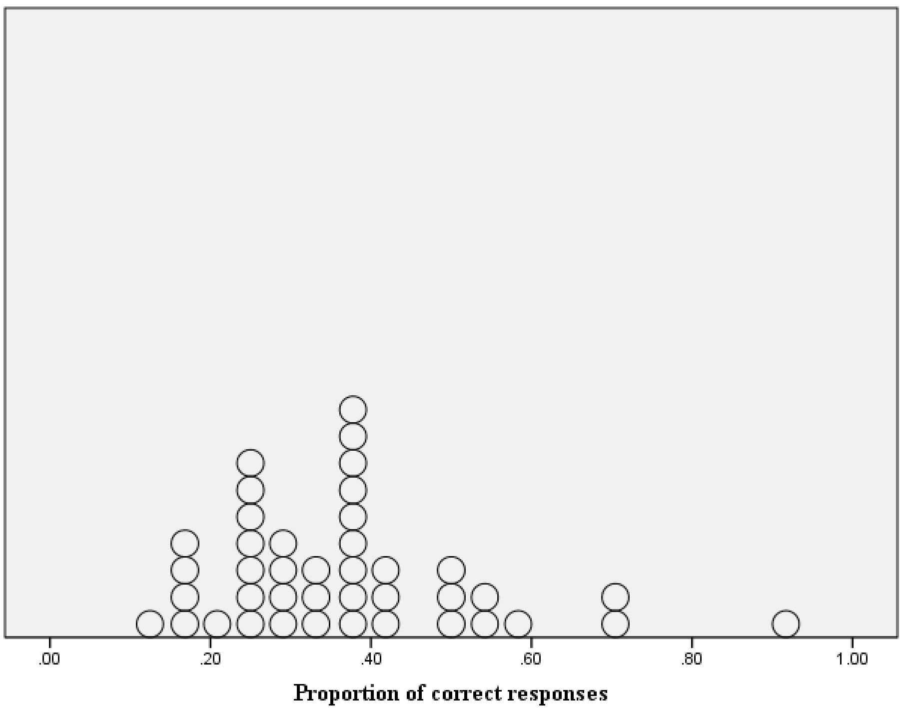

Figure 4.5: Simple dot plot of participants' performance in the 4AFC task, representing each individual's proportion of correct responses.

The overall proportion of guess attributions was 0.44 (SD = 0.28), the proportion of intuition attributions was 0.33 (SD = 0.18) and the proportion of memory attributions was 0.23 (SD = 0.2), indicating that participant felt that they were guessing on most of the trials. A one-way repeated-measures ANOVA showed this difference to be significant, $F(1.502, 61.597) = 6.422$, $p = .006$, $\eta_p^2 = 0.135$. Pairwise comparisons showed that participants used guessing significantly more than memory ($p = .011$) 95% CIs of the difference [0.04 0.38], and intuition significantly more than memory ($p = .035$), CIs of the difference [0.006 0.197], but there was no significant difference between their use of guessing and intuition ($p = .304$), CIs of the difference [-0.27 0.053]. Figure 4.6. The participants' average confidence in this task was 62.05 (SD = 8.06).

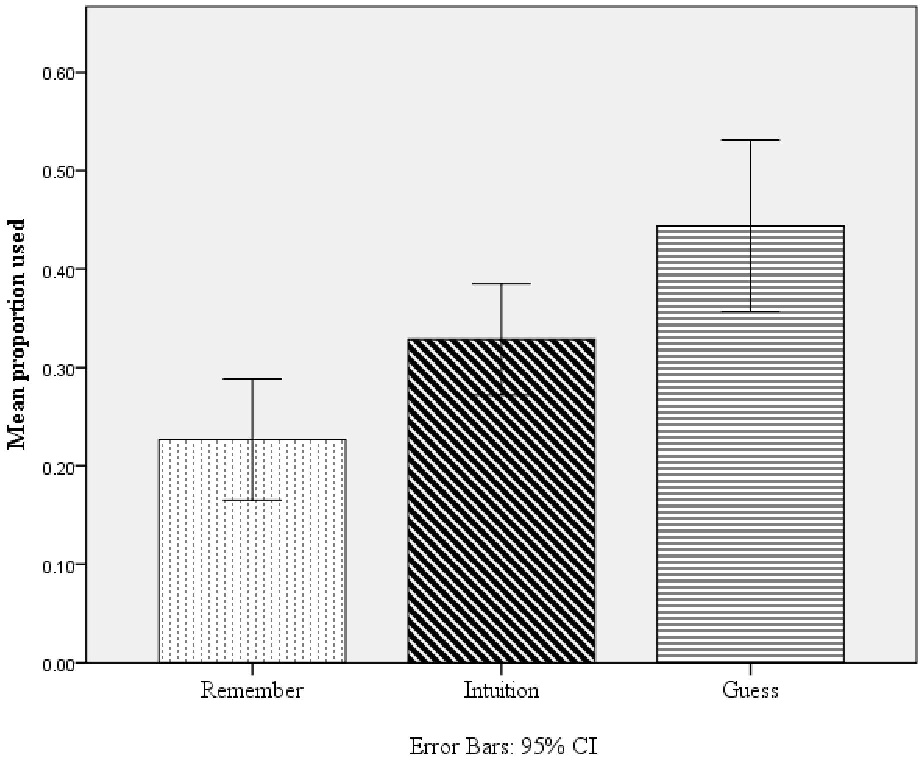

Figure 4.6: Mean proportion of guess, intuition and memory attributions used within the 4AFC task.

Performance was significantly above chance for all types of knowledge attributions: whether participants felt that they were guessing (*M* = 0.39, *SD* = 0.23), $t(40) = 3.982$, $p < .001$, one-tailed, 95%CIs [0.057 0.228], Cohen's $d = 0.622$, using their intuition (*M* = 0.45, *SD* = 0.21), $t(35) = 5.588$, $p < .001$, one-tailed, 95% CIs [0.112 0.281], Cohen's $d = 0.931$, or remembering (*M* = 0.57, *SD* = 0.31), $t(28) = 5.562$, $p < .001$, one-tailed, 95% CIs [0.195 0.439], Cohen's $d = 1.033$. These results suggest the presence of both implicit and explicit knowledge by the guessing criterion (Figure 4.7).

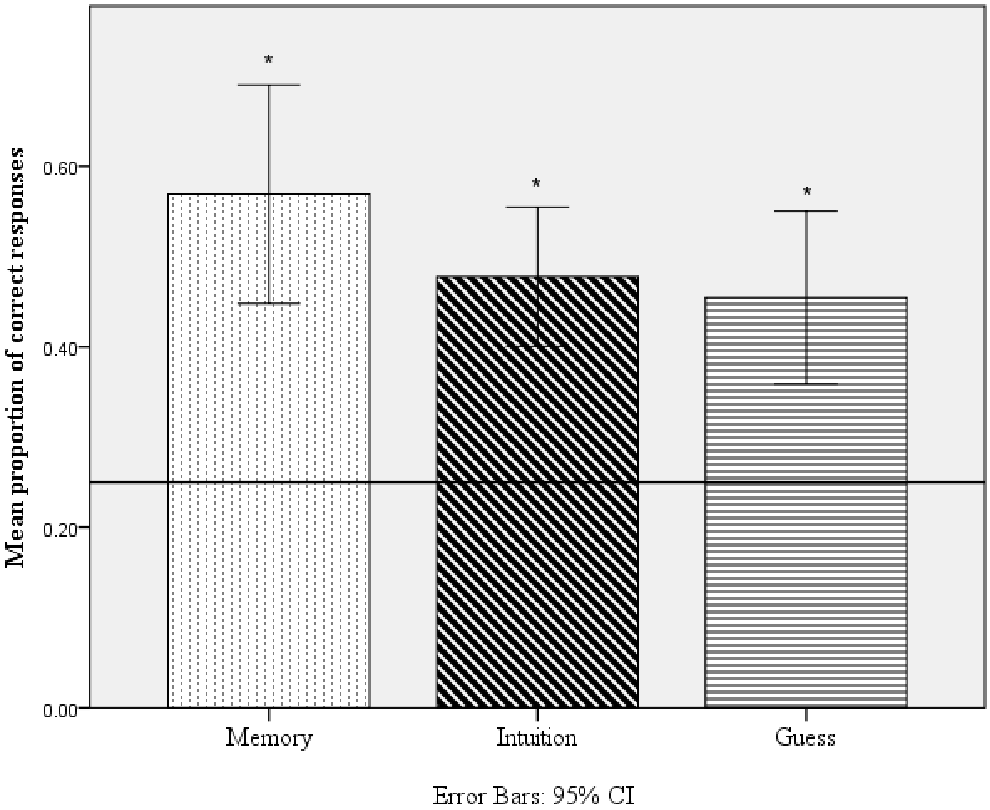

Figure 4.7: Mean proportion of correct responses separately for each type of knowledge attribution (guessing criterion). Line represents chance level (0.25). Conditions in which performance was significantly above chance are marked with one asterisk (*).

The zero correlation criterion indicates that knowledge was implicit, as no significant difference was found between participants' confidence in trials when they were correct (*M* =

62.6 *SD* = 8.39) and in trials when they were wrong (*M* = 60.46 *SD* = 12.4), t (39) = 1.117, p = .271, two-tailed, 95% CIs of the difference [-1.867 6.475], Cohen's d = 0.177, although, similarly to the 2AFC task results, the possibility that the confidence ratings may not have been sensitive enough to participants' confidence cannot be dismissed.

We carried out a paired-samples t-test comparing the proportion of correct responses in the first and second half of the test, to assess whether any in-test learning took place. The results were non-significant (p = .356), indicating that no learning took place during the test.

To assess whether participants preferred any specific triplet, we ran a one-way repeated-measures ANOVA on the number of times each of the four triplets was correctly completed in the four-choice completion task. There was a significant effect of triplet type, $F(3, 123)$ = 3.066, p = .031, η_p^2 = .070. Pairwise comparisons showed that this effect was driven by a difference between triplet 3, the most preferred, and triplet 4, the least preferred: p = .015, 95% CIs of the difference [0.114 1.552] (Figure 4.8).

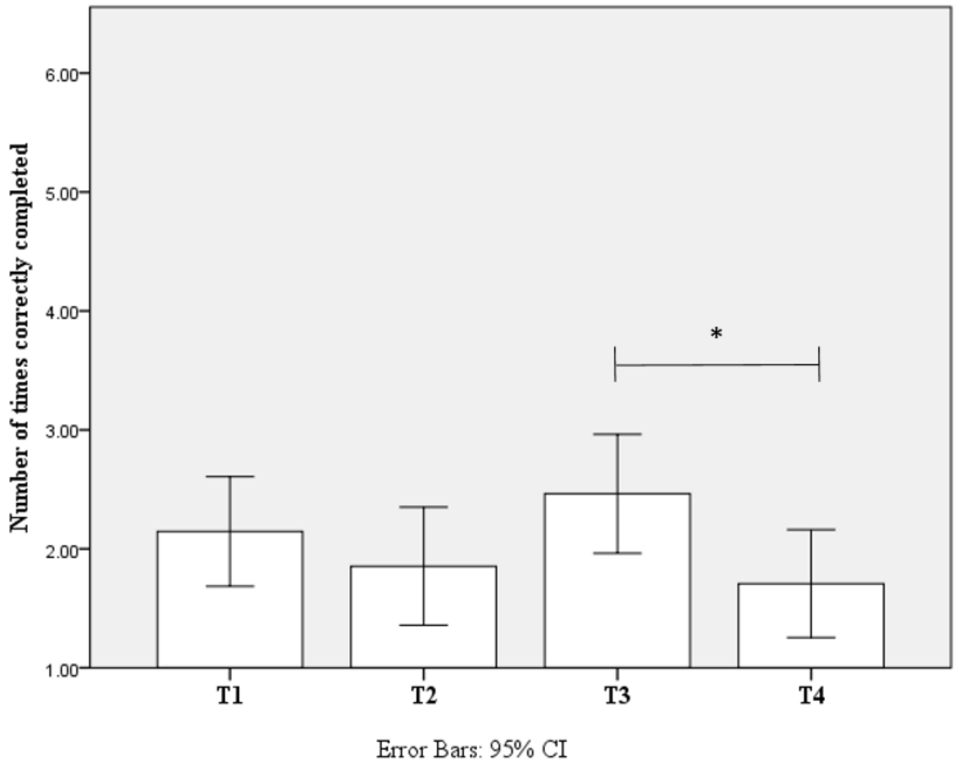

Figure 4.8: Average number of times each of the four triplets was correctly completed in the 4AFC task. Note: the maximum number of times each individual triplet could be chosen was six, as each triplet was repeated six times in the 4AFC task. Pairs of triplets which differed significantly according to pairwise comparisons are marked with an asterisk (*).

Additionally, we ran a correlational analysis between the proportion of correct responses in the 2AFC and 4AFC to verify whether our two forced-choice tasks tapped into the same knowledge acquired by participants during exposure. Interestingly, no significant correlation was found: $r = .186$, $p = .237$, $N = 42$, indicating that there was no relationship between scores on the 2AFC task and the 4AFC task (Figure 4.9).

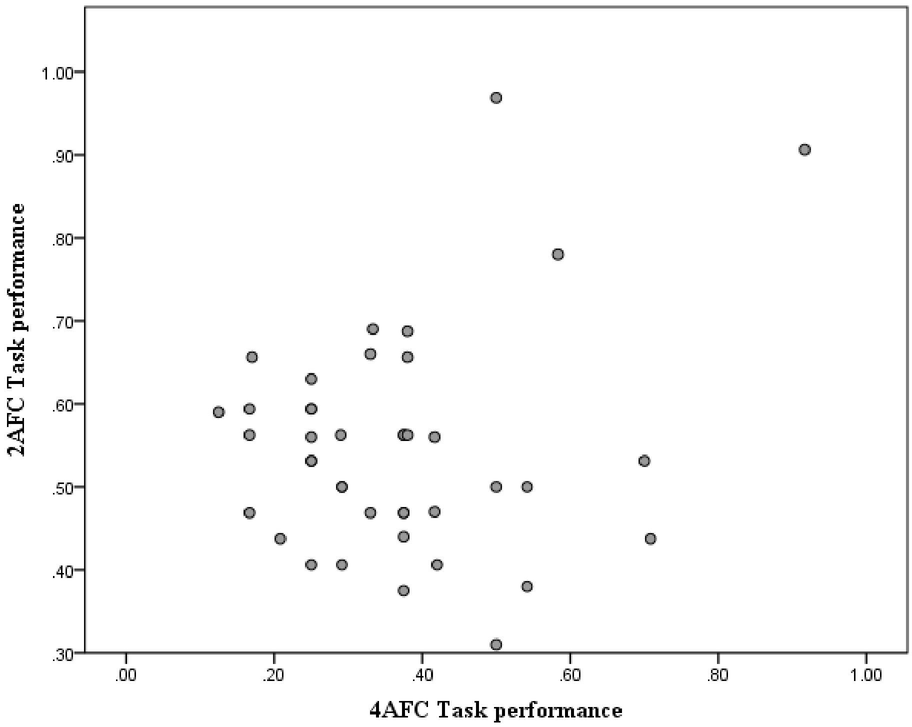

Figure 4.9: Scatterplot displaying the lack of a relationship between the proportion of correct responses in the 2AFC task and in the 4AFC task.

RSVP

RSVP data for 2 participants was missing due to a technical fault. Considering the one participant who was discarded from the analyses due to not having detected enough distractors during the exposure phase, data for 39 participants out of 42 who took part in the experiment were analysed.

Only correct Response Times (RTs) were analysed. In order to assess the correctness of RTs, we defined a time window for response which went from 150 msec to 650 msec after target onset. Any response times falling outside of this were considered incorrect. The time window was arrived at by adding 150 msec to the shape-to-shape duration (in this case 500 msec, as both the shape presentation and interval between shapes was 250 msec). Any response times faster than 150 msec were deemed too fast to be a response to the current shape, and were therefore classed as belonging to the previous shape, and therefore incorrect. This choice of time window for response also ensured no overlap with the subsequent time window. Furthermore, any RTs which were over three standard deviations above or below each individual participant's mean were considered outliers and discarded. During the test phase, for the sake of consistency, participants' first response was taken to be the intended one.

The overall proportion of correct responses, that is, the proportion of targets correctly detected in the RSVP task was 0.88 (SD = 0.08), indicating that participants were able to perform the task. In order to assess evidence of learning of the triplet structure through response times, a one-way repeated-measures ANOVA was carried out on correct response times to shapes in first, second and third position within the triplets. There was no significant effect of shape position, $F(2,76) = 2.061$, $p = .134$, $\eta^2_p = 0.051$, indicating that the knowledge of the triplet structure acquired by participants was not reflected in their response times. We also carried out a one-way repeated-measures ANOVA on the proportion of correct responses for the three target shape positions, and found no significant effect, $F(2,76) = 0.691$ $p = .504$, $\eta_p{}^2 = 0.018$. Descriptive statistics for the RSVP task are found in Table 4.1.

Dependent measure for SRTT	**Shape position within triplet**	**Mean (*SE*)**	**Confidence intervals around the mean**
Response Times	**First**	380.02 (5.50)	[368.882 391.157]
	Second	379.24 (5.93)	[367.231 391.243]
	Third	373.99 (5.03)	[363.805 384.174]
Proportion Correct	**First**	0.90 (0.02)	[.865 .927]
	Second	0.88 (0.02)	[.837 .913]
	Third	0.88 (0.02)	[.844 .912]

Table 4.1: Descriptive statistics for response times and proportion of correct responses in the RSVP Task for shapes in first, second and third position within a triplet.

It is important to note that, in a separate analysis, raw response times were also log transformed using the formula log(1/RT). This transformation had no impact on the results of the analysis and, for this reason, in order for our data to be in line with those of similar studies, we decided to focus on, and report, raw response times for this experiment.

Generation task

Of the 41 total participants whose data was analysed, 1 participant (representing 2.4% of the total participants) was able to reproduce two whole triplets, 5 participants (representing 12.2% of the total participants) were able to reproduce one whole triplet, and 35 participants (representing 85.4% of the total participants) could not reproduce any triplets at all. The specific triplets that were reproduced mirrored the results of our triplet preference analysis, with Triplet 4 being the least preferred, as Triplet 1 was reproduced three times in total, Triplet 2 was reproduced twice, Triplet 3 was reproduced three times, and Triplet 4 was not reproduced at all.

Correlations between the different measures of learning

In order to assess the relationship between our four different measures of knowledge, 2AFC task, 4AFC task, RSVP and generation task, we ran a correlation analysis between them. Our dependent variable for the forced-choice tasks was the proportion of correct responses, and for the generation task the number of whole triplets generated by participants. Because the RSVP data consisted of three data points per participant for Response Times (RTs) to shapes in position 1 (S1), position 2 (S2) and position 3 (S3) within a triplet, in order to obtain a measure that would capture performance in this task, we calculated the RT difference between S1 and S3 and took this as a measure of the extent of learning reflected in the RTs (which we refer to as RSVP Learning Index). We reasoned that, since learning in this task is thought to be reflected in longer RTs to shapes in position 1 than in position 3 within a triplet, a positive RSVP Learning Index would reflect some learning, whilst a negative index would reflect no learning.

The results of our correlation analysis are displayed in Table 4.2. We found significant positive correlations between Generation performance and 2AFCT and 4AFCT performance, indicating that better performance in the forced-choice tasks corresponded to a higher number of whole triplets generated by participants. There was also a significant positive relationship between 4AFCT performance and our RSVP Learning index, indicating that a larger proportion of correct responses in the 4AFC task corresponded to a larger RSVP Learning Index, that is, greater learning reflected through RTs.

		1	**2**	**3**	**4**
1 Generation performance	*r*	1	$.593^{**}$	.296	$.385^{*}$
	p		.000	.063	.012
	N	42	42	40	42
2 4AFC performance	*r*	$.593^{**}$	1	$.339^{*}$	.185
	p	.000		.032	.241
	N	42	42	40	42
3 RSVP learning index	*r*	.296	$.339^{*}$	1	.271
	p	.063	.032		.090
	N	40	40	40	40
4 2AFC performance	*r*	$.385^{*}$	.185	.271	1
	p	.012	.241	.090	
	N	42	42	40	42

Table 4.2: Correlation matrix illustrating the relationship between our four different measures of knowledge. Correlations significant at the 0.05 level (2-tailed) are marked with one asterisk (*) and correlations significant at the 0.01 level (2-tailed) are marked with two asterisks (**).

Given the presence of significant relationships between some of our variables, we carried out a Factor Analysis to assess the presence of different underlying constructs captured by our measures of learning. We used the Principal Components method based on Eigenvalues greater than 1. The results indicated that our four measures of knowledge all loaded onto one single factor, therefore no rotation was necessary. The fact that only one component was extracted was seen as consistent with the idea that the different, direct and indirect, measures used in this experiment all tap into one single construct, which we could refer to as "degree of statistical learning" acquired in the tasks. The single factor explained 52.83% of the variance, with factor loadings for the four individual items ranging from .606 to .842.

4.2.3 Discussion

In the 2AFC task participants performed significantly above chance, replicating the results of similar visual triplet learning studies (Turk-Browne et al., 2005; Fiser & Aslin, 2002b), as well as the results of Chapter 3 of this thesis. Participants performed at chance in trials when they were guessing and using their intuition, but above chance when they were using memory which, according to the guessing criterion, suggests that their knowledge was explicit (Zoltán Dienes, 2004; Ziori & Dienes, 2006). This was in contrast with results of no difference in confidence between correct and incorrect trials, which indicated implicit knowledge by the zero correlation criterion. We took this as an indication of explicit knowledge in this task, with some implicit knowledge. However, we recommend caution when interpreting these confidence ratings. In fact, we cannot exclude the possibility that they might have been influenced by individual bias, such as participants having low confidence, or high participant variability in using the scale, giving low statistical power.

In line with previous research (Bertels et al., 2015b; Bertels et al., 2012a), performance was also above chance in the 4AFC task, and this was a larger effect than for the 2AFC task, which could be indicative that this task might be more sensitive to participants' knowledge. Participants used significantly more guess and intuition attributions than memory attributions. This, together with the finding of above-chance performance when guessing, suggests implicit knowledge, intended as participants lacking awareness that they had knowledge. This was further reinforced by the lack of a difference between confidence when correct and when wrong.

Whilst findings of the 2AFC task were in line with previous suggestions of explicit knowledge in visual triplet learning (Bertels et al., 2015b; Bertels et al., 2012a), the fact that the 4AFC data pointed to the presence of implicit knowledge contradicts these authors, who used the 4AFC as their only task. This discrepancy in the knowledge type between the two tasks is an interesting finding, as is the lack of correlation between performance in the two measures. We believe it is indicative of the fact that participants found the 4AFC task more difficult than the 2AFC task, confirmed by the fact that their confidence was lower than in the 2AFC task. It is possible that the 2AFC task lent itself to the use of familiarity and recognition strategies for performance, as participants were required to evaluate and compare two whole triplets: a training triplet and a foil triplet. In contrast, the 4AFC task may have required more in-depth knowledge of the triplets, given that participants could choose any of four shapes to complete the test triplet. Furthermore, there is also the possibility that the cover task during exposure might have interfered with the development of explicit knowledge, a hypothesis which is in line with previous suggestions made in the context of Artificial Grammar Learning (Dienes & Scott, 2005). If this was the case, however, the cover task should have also made knowledge more implicit in the 2AFC task. Given that this experiment did not include a comparison of a single-task and dual-task group, it is very difficult to draw firm conclusions.

The lack of a correlation between the proportion of correct responses in the two tasks was also surprising. In line with our suggestion above, this could either indicate that the two tasks required different strategies for successful performance, or that, whilst participants used explicit knowledge in the 2AFC task, the 4AFC task used at least some implicit knowledge and different participants may have used these two different knowledge types to different extents. This is an interesting possibility which should be investigated further in future research.

Another possible explanation for the failed replication of Bertels et al's 4AFC results (2015b) could be that the authors used different visual presentation parameters to the ones we used in this study. In fact, they trained their participants with roughly four times the amount of exposure trials we used in this experiment, but at a faster stimulus presentation speed. Our choice of amount of exposure and presentation speed in this experiment was based on our successful use of the triplet learning paradigm in Chapter 3 of this thesis, where we found that triplets can be learned at a presentation speed of 400 msec and with a short exposure. The possibility that we failed to replicate Bertels et al., (2015b) due to the amount of exposure we gave our participants is something that we addressed in our next experiment, as it is possible that, when given more training, participants are able to develop explicit knowledge in the more difficult 4AFC task.

Some methodological considerations regarding the 4AFC task are also necessary. This task presented participants with the same triplet with a shape missing in either first, second or third position. For example, one trial could have presented a triplet with a missing shape in third position, and another trial could have presented the same triplet, but with a missing shape in a different position, therefore providing the correct answer regarding the earlier trial. This means that, as participants progressed through the task, it would have been possible for a very attentive participant to obtain the correct answer to one trial through observation of the triplet in a previous trial and to, at least partially, deduce what the triplets were. We have had occasional spontaneous reports by some of our participants that they were actively attempting to work out the "solution" to the task by comparing the test stimuli in one trial to those in the previous trial. To assess whether learning was taking place within the 4AFC task, we compared the proportion of correct responses in the first and second half of the test and found no significant difference, therefore within-task learning was not a problem in the present experiment. Nevertheless, this possibility is something that authors should be aware of in future studies. We suggest that the 4AFC task could encourage the development of explicit knowledge of the triplet structure in some participants, and therefore recommend caution when using it in experiments aiming to measure implicit knowledge. In the context of the present experiment, we discarded this possibility, given that knowledge in this task appeared to be more implicit than in the 2AFC task, and given that there was no evidence for learning during the test phase.

In an analysis of triplet preference, we found that our participants correctly completed triplet number three significantly more times than triplet number four. This triplet preference effect suggests the presence of participant biases towards either certain shapes or certain arrangements of shapes. We could tentatively suggest that this may be due to the possibility to verbally label those shapes, therefore making them more memorable. Further to findings of triplet preference effects in Chapter 3 of this thesis, in the present experiment we re-arranged our shape triplets, aiming to balance the preference between different triplets within the trained and the untrained language. It is interesting to see that a preference for certain triplets remained despite this precaution. It should be noted that, despite the changes made to the triplets in the present experiment, two of the shapes contained in Triplet 3 remained the same between our experiment in Chapter 3 and the present experiment. This leads us to suggest that the preference effect observed may be due to certain characteristics of those two particular shapes (see Appendix E.6 for a visual comparison of the two shape languages used in this thesis). We speculate that participants might find it easier to verbally label these shapes, which could make them more memorable. Future research using this visual triplet learning paradigm should investigate the reasons underlying preferences towards certain shapes, and develop visual stimuli which are less subject to these biases.

Unlike Bertels et al., (2015b), we also failed to find a difference in response times between shapes in first, second and third position within a triplet in the RSVP task, indicating that this task did not detect any of the participants' knowledge about the triplet structure, despite performance in the 2AFC and 4AFC tasks indicated that knowledge had, indeed, been acquired. Indirect tasks are considered particularly sensitive to implicit knowledge, which would not otherwise be detected through forced-choice tasks (Kim et al., 2009). Interestingly, although the guessing criterion detected the presence of implicit knowledge in our 4AFC task, no knowledge was detected by the RSVP task. The reasons for this failure to replicate the response-time effect in the RSVP should be explored more in depth. However, the findings we obtained also reinforce our confidence that the guessing and zero correlation criteria detected all the relevant knowledge held by our participants.

The discrepancy between the visual presentation parameters used in this study and those used by Bertels et al., (2015b) might be responsible for the lack of a response time effect in the RSVP observed in this experiment. As mentioned above, this is something which we decided to address in our next experiment. However, we also suggest that the RSVP task might be affected by two methodological issues which deserve discussion surrounding the data analysis strategy and participants' retention of the target shape within each trial.

Previous research has not provided a large amount of detail regarding their data analysis strategies in this task (Turk-Browne et al., 2005; Kim et al., 2009; Bertels et al., 2012b; Bertels et al., 2015b). For the purpose of discriminating correct and incorrect responses, we adopted a time window for response to each target. Our calculation for this time window was based on an estimate of the minimum time required to make a response and the length of presentation of each shape. However, it needs to be pointed out that the adoption of a time window does not completely eliminate the possibility that valid, but longer, response times could have fallen outside of this time window and therefore not have been analysed. We suggest that careful consideration is needed by authors when deciding on data analysis strategies for this task, and that it is important to provide full details of the strategy adopted in order to ensure successful replication and comparability across studies. Crucially, in our data analysis strategy, we assumed that any response time provided by participants is a response time to the target, which leads on to the next methodological concern around the RSVP task.

There is also the possibility that participants might have forgotten what target shape they were looking for within a test sequence and, therefore, responded to a different shape instead of the correct target shape. This suggestion is based on occasional spontaneous reports by participants that, sometimes, they forgot what the target shape was. Although such spontaneous comments by participant were very rare, this is something that was difficult to control experimentally in this task, but that could have affected the results. Interestingly, previous research using this task makes no mention of such an occurrence during the RSVP experiments conducted (Turk-Browne et al., 2005; Kim et al., 2009; Bertels et al., 2012b; Bertels et al., 2015b), and therefore we have no term of comparison in this respect. Future research using an RSVP task in triplet learning should attempt to counteract this issue around forgetting the target shape and to systematically measure these forgetting rates. For example, by obtaining verbal reports regarding this from participants on each RSVP trial. Given the failure of our RSVP task to detect our participants' knowledge, no conclusion could be drawn in this experiment regarding the use of a dissociation between direct and indirect measures to learn about the nature of participants' knowledge.

Another difference between our experiment and Bertels et al.'s (2015b) was the order in which tasks were administered after exposure. Whilst the authors administered their RSVP after exposure, we administered it last, after the 2AFC task and the 4AFC task. Our choice of order of tasks was based on our aim to test knowledge in the forced-choice tasks directly after exposure. In fact, the RSVP streams are effectively shorter fragments of exposure, and therefore could have provided participants with extra training, and affected their performance and knowledge status in the forced-choice tasks. In a scenario in which the RSVP was administered first, and detected participant knowledge, it would have been less likely for the forced-choice tasks to not detect any knowledge, given the fact that participants had seen more instances of the correct triplets during the RSVP. We hold that placing the RSVP after exposure would have made it less likely to find any dissociation between the direct and indirect tasks. However, it is important to acknowledge that the opposite argument could have also been made regarding our choice of order of tasks. In fact, it could have been claimed that taking part in the forced-choice tasks could have reduced the amount of implicit knowledge held by participants, making it difficult to then measure this through the RSVP task. We respond to this potential counter-argument by suggesting that any knowledge held by our participants, implicit or explicit, should have been measurable through the RSVP task, therefore we suggest that the order of administration of tasks was not a factor responsible for the failure to obtain a learning effect through response times in the present experiment. Furthermore, this experiment found evidence of implicit knowledge in the 4AFC task, indicating that implicit knowledge was available in this experiment to be potentially detected by the RSVP.

Nevertheless, we suggest that the order of tasks is a methodological challenge in experiments comparing direct and indirect measures. In fact, there is potential for one measure to affect the subsequent measure using both types of task order: whilst, if the direct measure is administered first, this could affect performance on the indirect measure, the reverse is also true. A possible avenue to address this issue in future research could be to counter-balance the order of administration of direct and indirect measures.

Important findings emerged from our generation data. The results of this task suggest that, despite the above-chance performance in the 2AFC and 4AFC tasks, participants were not able to successfully re-create the four triplets. Shanks & St John (1994) proposed that generation tasks have a greater ability than other tasks to detect conscious knowledge. In the present study, our generation task found that no conscious knowledge, intended as explicit recollection, was present. Although the finding of poor performance in our generation task appears at odds with the successful performance obtained in SRTT studies (Bischoff-Grethe et al., 2004; Norman & Price, 2010; Fu et al., 2008a; Fu et al., 2013), we argue that the two tasks are not comparable, due to the profound differences in the two types of statistical learning paradigms: motor an non-motor. Within non-motor visual statistical learning, our task most closely resembles the matching task developed by (Kim et al., 2009). However, we argue that our task is not comparable with these authors either, as, in that experiment, one shape was provided as a cue, and participants had eleven shapes to choose from to complete the triplet, therefore tapping into recognition more than recollection mechanisms. As such, our implementation of the generation task is novel within visual statistical learning, and we suggest that it is as close as possible to genuine generation of the shapes.

The results from the PDP, the guessing and zero correlation criteria that we obtained in Chapter 2 and 3 of this thesis so far indicated that participants mostly acquire explicit knowledge in out statistical learning tasks, in the sense that they are able to control the expression of knowledge and that they are aware of the knowledge they hold. In contrast, the findings of this experiment strongly suggest that performance in forced-choice tasks, which some have considered "explicit" tasks (Turk-Browne et al., 2005; Kim et al., 2009) taps into strategies for performance, such as recognition and familiarity, which do not coincide with explicit recollection. This has important implications for the understanding of measures of implicit and explicit statistical learning in our research and further highlights the importance of clear operationalisations of conscious knowledge. Future research looking to investigate implicit and explicit knowledge in sequential regularities learning should make wider use of generation tasks to more fully assess the nature of knowledge. Although, due to the methodological constraints imposed by the RSVP, this was a visual-only experiment, future studies should also focus on the development of generation tasks for use in the auditory modality.

4.3 Direct and indirect measures in adults – Version 2

Our experiment on direct and indirect measures of knowledge in adults (Version 1) did not successfully replicate findings of previous research regarding response-time differences between shape positions in the RSVP (Turk-Browne et al., 2005; Kim et al., 2009; Bertels et al., 2012b; Bertels et al., 2015b) and explicit knowledge in the 4AFC task (Bertels et al., 2012b; Bertels et al., 2015b). Although we put forward a number of hypotheses for the lack of consistency between our experiment and previous research, some of which based on the characteristics of the tasks used, it was necessary to also investigate the possibility that our failed replication could be due to the difference in the experiment parameters between our research and previous authors', namely, the amount of exposure provided to participants and the speed of presentation of the visual stimuli. We were particularly interested in how our findings compared to those of Bertels et al. (2015a), in that these authors used a 4AFC task and an RSVP task with a sample of children, which was also our goal in the present chapter. For this reason, despite being very similar to Version 1, this experiment used the same parameters as Bertels et al., (2015a) with regards to the amount of exposure/ training, and the speed of visual presentation during the exposure and test phases. Furthermore, in order to maximise learning in this task, we also removed the distractor task during the exposure phase, in the eventuality that this might have reduced the amount of knowledge acquired by participants, and altered its nature, in Version 1.

4.3.1 Materials and methods

4.3.1.1 Participants

Forty-two participants took part in the experiment. The majority of participants were undergraduate students at the University of Lincoln who took part in the experiment in exchange for research credit points. A minority of participants were members of the public who participated voluntarily. Demographic information was missing for 11 participants. Of the remaining 31 participants, 7 were males (age range = 18- 48 years, mean age = 24.00 *SD* = 10.75) and 24 were females (age range = 18-50 years, mean age = 20.63, *SD* = 6.32). First language and dyslexia data was only available for 19 participants. All of these spoke English as their first language and no participants had a diagnosis of dyslexia. All participants had normal or corrected to normal vision and no medical conditions which could have affected their participation or the validity of the data.

4.3.1.2 Ethics

The study received ethical approval from the University of Lincoln Psychology Research Ethics Committee (see Appendix A for ethical approval form and full details of ethical approval). Participants provided full informed consent and were free to withdraw from the study at any point without providing any motivation, or to withdraw their data at a later point. At the end of the experiment participants were fully debriefed, verbally and in writing (See Appendix E.2 for participant information sheet, consent form and written debrief form).

4.3.1.3 Stimuli

Stimuli for this version of the experiment were identical to Version 1, with the exception of changes in parameters outlined in the Exposure Phase and Test Phase sections.

4.3.1.4 Apparatus

The apparatus used for this version of the experiment is identical to that of Version 1 in this chapter.

4.3.1.5 Procedure

4.3.1.5.1 Exposure phase

For consistency with the exposure phase used by Bertels et al. (2015a), the original number of exposure trials which we used in Experiment Version 1 was quadrupled, thus obtaining 1152 exposure trials (shapes) and the speed of presentation was shortened: each shape was on screen for 250 msec and the ITI was 250 msec. Furthermore, in order to maximise learning, and differently to Bertels et al., (2015a), we also removed the cover task from this exposure phase. Participant instructions were the same as those used in our previous visual experiments: "You will see a series of shapes. Please watch attentively. Press a key to see the shapes". The exposure stream now lasted 9.6 minutes. We aimed to investigate whether, with an increased amount of learning, the 4AFC task would make use of explicit knowledge, and whether a difference in response times to shapes in first, second and third position would be observed in the RSVP task.

4.3.1.5.2 Test phase

2AFC Task

The 2AFC task was identical to that of Version 1 of the experiment, with the exception that each shape was on the screen for 250 msec with an ITI of 250 msec.

4AFC Task

The 4AFC completion task was identical to that of Version 1 of the experiment except for the shape presentation times: each shape was presented for 250 msec with an ITI of 250 msec.

RSVP task

The RSVP task was identical to that of Version 1 of the experiment. Refer to Appendix E.3 for on-screen task instructions.

Generation task

The generation task was identical to that of Version 1 of the experiment.

Overall, the experiment lasted approximately 45 minutes. Refer to Appendix C for standardised verbal instructions for all tasks.

4.3.2 Results

2AFC Task

Data for one participant for the 2AFC task was lost due to a technical fault, therefore, 2AFC data for 41 participants was analysed.

The mean proportion of correct responses in the 2AFC task was 0.59 (*SD* = 0.15). A one-sample t-test revealed that this was significantly above chance (0.5), $t(40) = 3.902$, $p < .001$, one-tailed, 95% CIs [0.027 0.153], Cohen's $d = 0.609$, indicating that participants had successfully learned the statistical structure of the stimuli. See Figure 4.10 for a dot plot of performance in the 2AFC task.

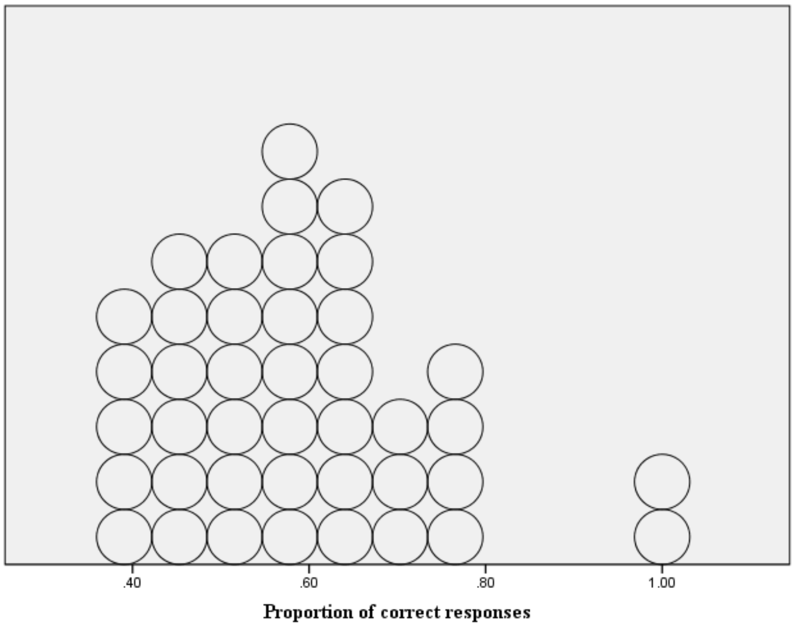

Figure 4.10: Simple dot plot of participants' performance in the 2AFC task, representing each individual's proportion of correct responses.

Overall, participants made use of all three knowledge attributions, as the proportions were similarly distributed between guess (0.33, *SD* = 0.2), intuition (0.39, *SD* = 0.2) and memory (0.35, *SD* = 0.24). Performance was at chance when participants were guessing, $t(38) = 0.968$, $p = .170$, one-tailed, 95% CIs [-0.050 0.115], Cohen's $d = 0.155$, and when they were using their intuition, $t(37) = 2.529$, $p = .008$,one-tailed, 95% CIs [-0.056 0.179], Cohen's $d = 0.410$, and above chance when they were using their memory, $t(37) = 3.395$, $p = .001$, one-tailed, 95% CIs [0.038 0.213], Cohen's $d = 0.551$. This indicated that knowledge was explicit by the guessing criterion (Figure 4.11), a finding which was further reinforced by results of the zero correlation criterion, showing that participants' confidence was significantly higher in trials when they were correct ($M = 68.44$ $SD = 10.25$) than in trials when they were wrong ($M = 65.61$ $SD = 9.54$), $t\ (28) = 2.468$, $p = .020$, two-tailed, 95% CIs of the difference [0.48148 5.17968], Cohen's $d = 0.284$.

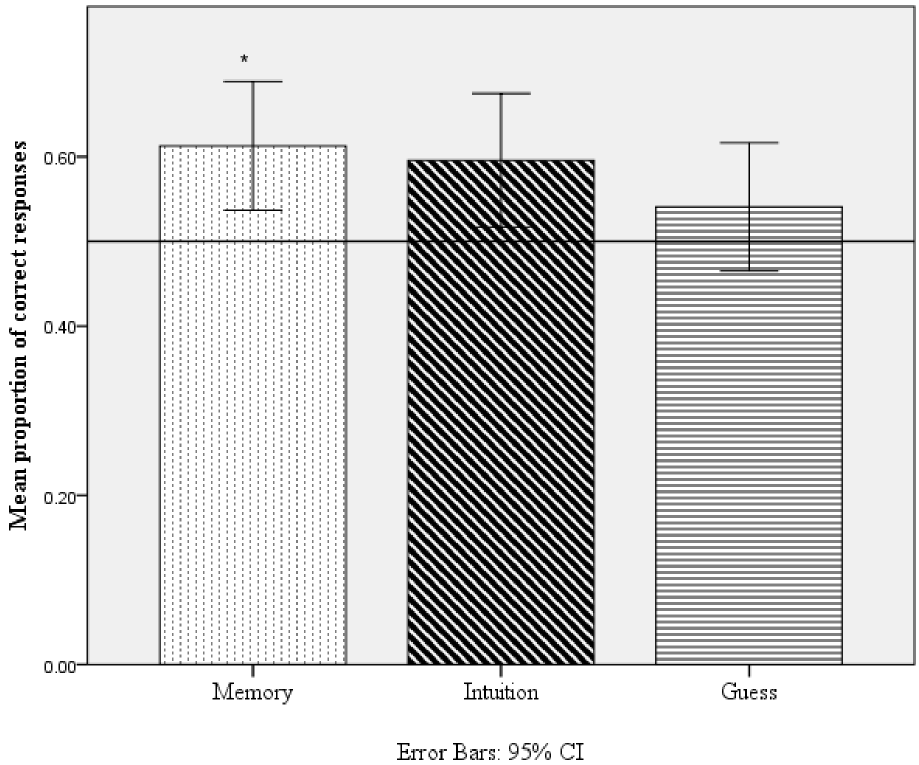

Figure 4.11: Mean proportion of correct responses separately for each type of knowledge attribution (guessing criterion). Line represents chance level (0.5). Conditions in which performance was significantly above chance are marked with one asterisk (*).

To assess the possibility of within-test learning, we carried out a paired-samples t-test between the proportion of correct responses in the first and second half of the test. This was non-significant (p = .656), showing that no learning took place in the course of the test.

In order to assess whether participants' choices were biased towards specific shape triplets, a one-way repeated-measures ANOVA was carried out on the number of times each of the four triplets, in L1 (the training language) and L2 (the untrained language) was chosen, regardless of correctness. There was a significant effect of triplet type for L1 triplets, $F(2.125, 84.993) = 3.146$, $p = .045$, $\eta_p^2 = 0.073$ (Greenhouse-Geisser corrected), but none of the Bonferroni-corrected post-hoc tests were statistically significant. No significant effect of triplet type was found for L2 triplets, $F(3, 117) = 2.01$, $p = .116$, $\eta_p^2 = 0.049$, indicating that participants were not biased towards choosing a specific triplet irrespective of correctness.

4AFC Task

The mean proportion of correct responses in the 4AFC task was 0.45 ($SD = 0.17$), and this was significantly above chance (0.25), $t(41) = 7.466$, $p < .001$, one-tailed, 95% CIs [0.127 0.266], Cohen's $d = 1.152$, suggesting that participants were able to successfully use their knowledge of the triplet structure in this task. See Figure 4.12 for a dot plot of performance in the 4AFC task.

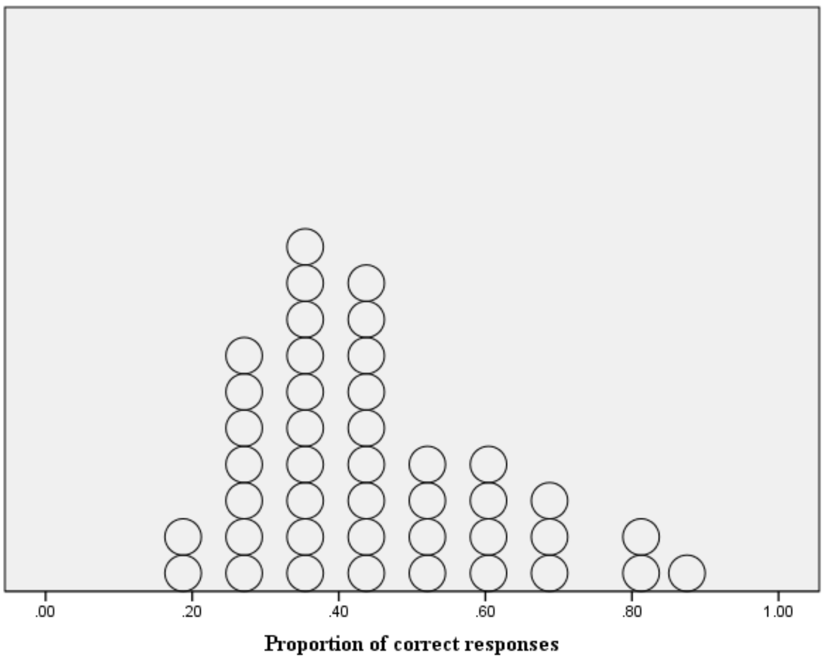

Figure 4.12: Simple dot plot of participants' performance in the 4AFC task, representing each individual's proportion of correct responses.

Participants mostly felt that they were using their intuition during this task, with an overall proportion of intuition attributions of 0.42 ($SD = 0.23$). The overall proportion of guess attributions was 0.30 (*SD* = 0.23), and the proportion of remember attributions was 0.36 (*SD* = 0.28). Performance was significantly above chance for all types of knowledge attributions: whether participants felt that they were guessing, $t(40) = 3.058$, $p = .002$, one-tailed, 95% CIs [0.029 0.212], Cohen's $d = 0.478$, using their intuition, $t(38) = 4.811$, $p < .001$, one-tailed, 95% CIs [0.087 0.279], Cohen's $d = 0.77$, or remembering, $t(36) = 6.563$, $p < .001$, one-tailed, 95% CIs [0.238 0.471], Cohen's $d = 1.079$. By the guessing criterion, this would suggest that both implicit and explicit knowledge were present (Figure 4.13). The zero correlation criterion indicated that knowledge was explicit, as participants' confidence was significantly higher in trials when they were correct ($M = 68.78$ $SD = 11.07$) than in trials when they were wrong ($M = 63.23$ $SD = 8.46$), $t(41) = 4.092$, $p < .001$, two-tailed, 95% CIs [2.810 8.285], Cohen's $d = 0.639$.

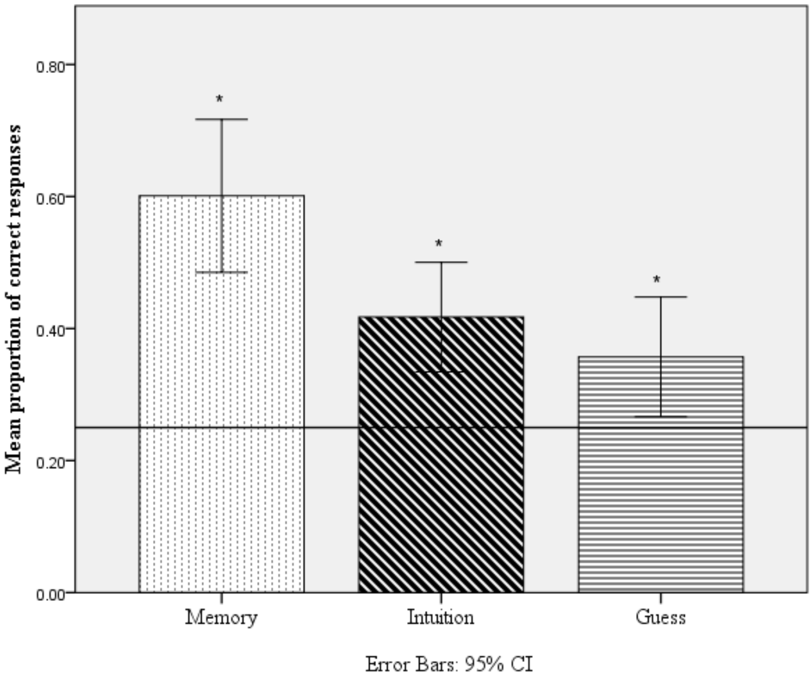

Figure 4.13: Mean proportion of correct responses separately for each type of knowledge attribution (guessing criterion). Line represents chance level (0.25). Conditions in which performance was significantly above chance are marked with one asterisk (*).

To assess whether any in-test learning took place, we carried out a paired-samples t-test comparing the proportion of correct responses in the first and second half of the test. The results were non-significant (p = .793), indicating that no learning took place during the test.

Potential preferences for any specific triplet were assessed by a one-way repeated-measures ANOVA on the number of times each of the four triplets was correctly completed in the four choice completion task. The effect of triplet type was significant, $F(3,123) = 3.777$, $p = .012$, $\eta_p^2 = 0.084$. Pairwise comparisons showed that this effect was driven by a significant difference between triplet three and triplet four (p = .020), 95% CIs of the difference [0.123 2.067] (Figure 4.14).

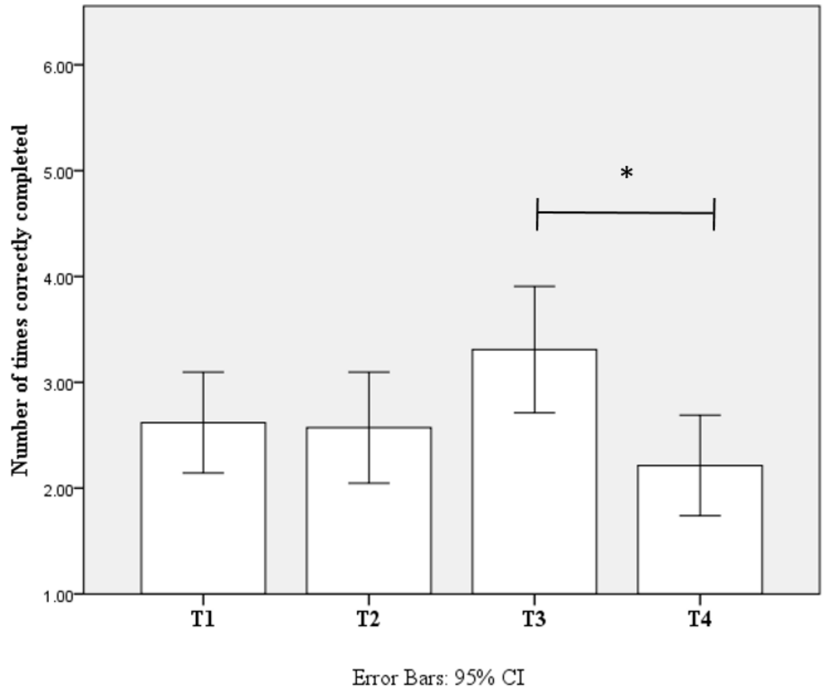

Figure 4.14: Average number of times each of the four triplets was correctly completed in the 4AFC task. Note: the maximum number of times each individual triplet could be chosen was six, as each triplet was repeated six times in the 4AFC task. Pairs of triplets which differed significantly according to pairwise comparisons are marked with an asterisk (*).

In order to verify that our 2AFC and 4AFC tasks tapped into similar knowledge acquired during exposure, we carried out a Pearson correlation between the proportion of correct responses in the two tasks. There was a significant positive correlation, with better performance in the 2AFC task corresponding to better performance in the 4AFC task, $r = .542$, $p < .001$, $N = 41$ (Figure 4.15).

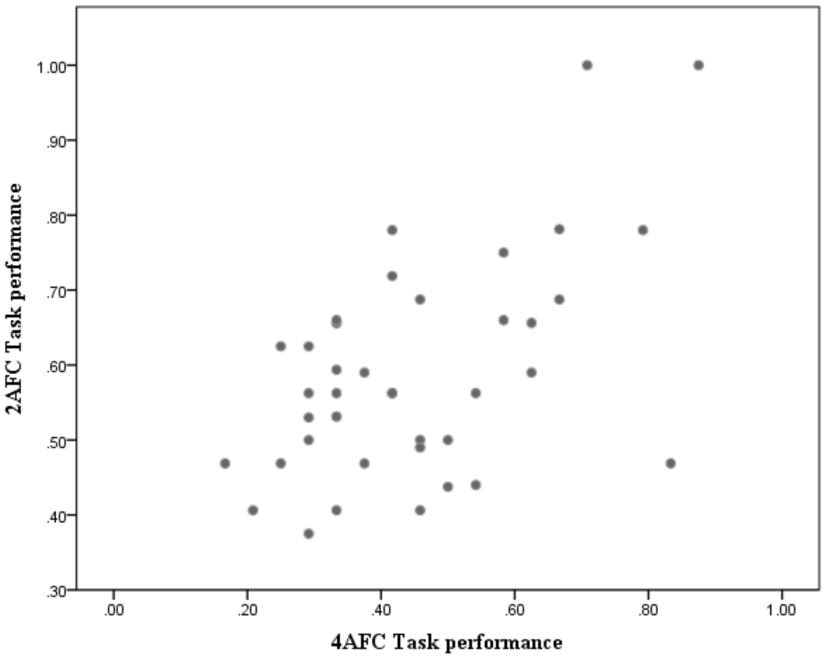

Figure 4.15: Scatterplot displaying the relationship between the proportion of correct responses in the 2AFC task and in the 4AFC task.

RSVP

Our data cleaning and data analysis strategy for the RSVP was the same as our Version 1 of this experiment.

The one-way repeated-measures ANOVA comparing response times to shapes in first, second and third position within the triplets showed a significant effect of shape position, $F(2,80)= 6.118$, $p= .003$, $\eta^2_p= 0.133$. Pairwise comparisons showed that responses to shapes in third position (M = 368.16 SE = 6.39) were significantly faster than to shapes in first position (M = 377.86 SE = 5.62), (p = .007), 95% CIs of the difference [2.304 17.094]. The one-way repeated-measures ANOVA using proportion of correct responses as a dependent variable showed no significant effect of shape position, $F(1.737, 69.482) = 0.124$, $p = .856$, $\eta^2_p = 0.003$ (Greenhouse-Geisser corrected). Average RTs for shapes in first, second and third position are shown in Figure 4.16.

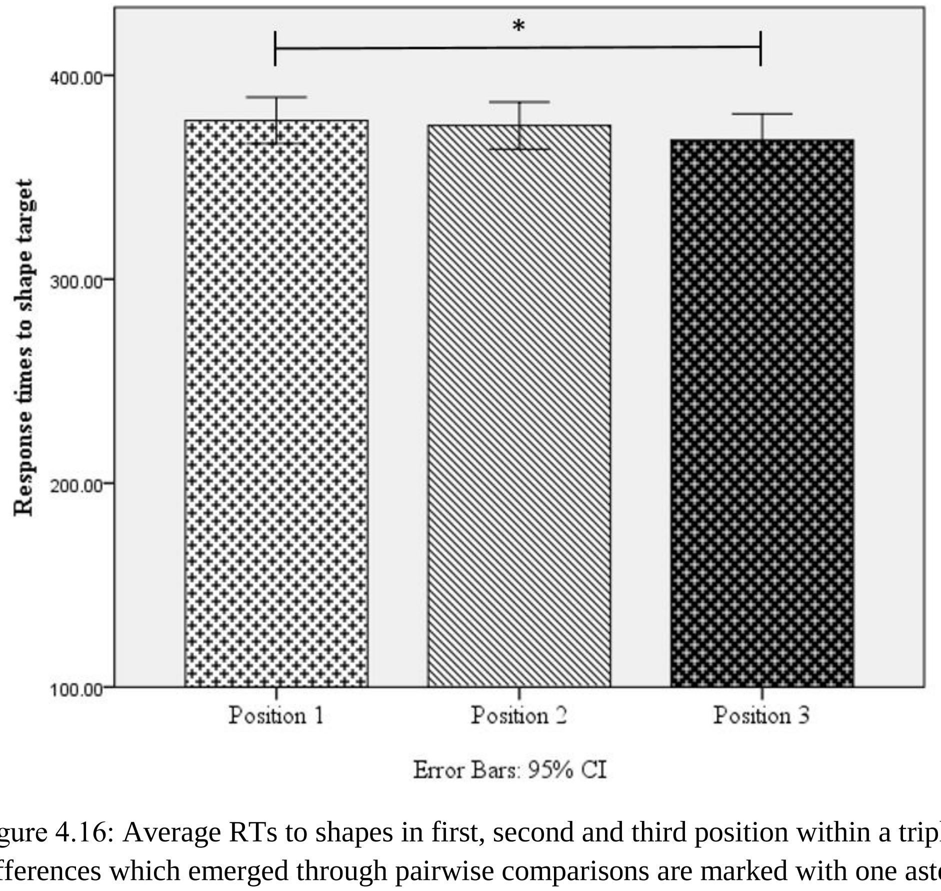

Figure 4.16: Average RTs to shapes in first, second and third position within a triplet. Significant differences which emerged through pairwise comparisons are marked with one asterisk (*).

Generation task

Participants' generation performance improved from Version 1 of the experiment. Whilst in Version 1, 85.4% of participants could not generate any triplets, in Version 2 this was reduced to 56.10%, indicating that the larger amount of training improved participants' recollection of the triplets and their ability to reproduce them in the generation task. Table 4.2 displays generation performance frequencies.

Number of whole triplets reproduced	**Number of participants**	**Percentage of participants out of total**
0	23	56.10 %
1	13	31.71 %
2	3	7.31 %
3	2	4.88 %

Table 4.3: Performance frequencies for the generation task

Similar to Version 1 of the experiment, these results also mirrored the results of the triplet preference analysis, with Triplet 3 being the most preferred, and Triplet 4 being the least preferred. In fact, triplets 1 and 2 were reproduced 7 times, Triplet 3 was reproduced 11 times, and Triplet 4 was not reproduced at all.

Correlations between the different measures of learning

In the same way as for experiment Version 1, we carried out correlations between our different measures of knowledge used in this experiment (Table 4.4). Surprisingly, the only significant correlation that we observed was between Generation performance and 2AFC task performance. Given that no other correlations were significant, there were no sufficient grounds to carry out a factor analysis for this version of the study.

		1	2	3	4
1 2AFC performance	*r*	1			
	p				
	N	41			
2 Generation performance	*r*	.470**	1		
	p	.002			
	N	40	41		
3 4AFC performance	*r*	.241	.208	1	
	p	.128	.192		
	N	41	41	42	
4 RSVP learning index	*r*	-.075	.049	.044	1
	p	.644	.766	.787	
	N	40	40	41	41

Table 4.4: Correlation matrix illustrating the relationship between our four different measures of knowledge. Correlations significant at the 0.01 level (2-tailed) are marked with two asterisks (**).

4.3.3 Discussion

In line with similar visual triplet learning studies (Turk-Browne et al., 2005; Fiser & Aslin, 2002b), participants successfully acquired knowledge of the visual triplets in this task. Performance in the 2AFC task was significantly above chance and this was a larger effect than in our Version 1 of this experiment. We attribute this to the greater amount of training that participants received in this version of the experiment and to the fact that no distractor task was given during exposure. The guessing criterion indicated that the knowledge acquired during exposure was held explicitly. In fact, performance was at chance in trials in which participants were guessing and when they were using their intuition and above chance in trials when they claimed that they were using memory. This finding was further corroborated by the results of the zero correlation criterion, indicating that participants' confidence was significantly higher in trials when they were correct than in trials when they were wrong. Based on these findings, we suggest that the more knowledge participants acquire in the task, the better able they are to track this knowledge. This is in line with suggestions made in the context of the SRTT paradigm that knowledge becomes more available to conscious access with larger amounts of training (Remillard & Clark, 2001; Fu et al., 2010b; Fu et al., 2008b), but see (Wilkinson & Shanks, 2004b).

Performance in the 4AFC task was significantly above chance. This was a larger effect than the 2AFC in this version of the task and also a larger effect than 4AFC performance in Version 1 of the task, which, again, we attribute to the greater amount of training provided in this experiment. Similar to Version 1 of the task, performance was above chance for all knowledge attributions, whether participants were guessing, using their intuition or remembering. By the guessing criterion, this would indicate that both implicit and explicit knowledge are present. There is a possibility that participants may find this task more difficult than the 2AFC task, which might lead them to feeling that they are guessing even in trials when they are correct. Results of the zero correlation criterion indicated explicit knowledge, as participants' confidence was higher in correct trials than incorrect trials.

Increasing the amount of training in this task seems to have made participants' knowledge more explicit than in Version 1 of the experiment, as shown by the difference in confidence between trials answered correctly and incorrectly. Nevertheless, the guessing criterion still showed implicit knowledge, which could be resulting from the fact that, even with a greater amount of training, participants still perceived the 4AFC task as more difficult than the 2AFC task, making them unable to fully track their knowledge.

It is also interesting that, when more training was given, the 2AFC and 4AFC tasks were found to correlate. In Version 1 of the experiment, we attributed the lack of a correlation between the two tasks to the fact that they might tap into different strategies for successful performance. Whilst we still support this explanation, we also suggest that, given the greater difficulty of the 4AFC task, more training is needed for it to detect knowledge of the triplets as well as the 2AFC, and therefore for the tasks to both tap into the same type of knowledge and to correlate. Alternatively, following the suggested additional interpretation of the lack of correlation that we observed in Version 1 of this experiment, it is possible that the greater training in the current version led to more explicit knowledge in the 4AFC task, which is reflected in the higher confidence ratings, and this leads to a stronger correlation with the explicit 2AFC task results. Therefore, the correlation between the two measures could be driven by the similarity, or lack thereof, of the type of knowledge.

In our RSVP task participants responded significantly faster to shapes in third position than shapes in first position within a triplet, and therefore the knowledge acquired by our participants was reflected in their response times, replicating previous findings obtained with this task (Turk-Browne et al., 2005; Kim et al., 2009; Bertels et al., 2012b; Bertels et al., 2015b). Comparing the results of Version 1 and Version 2 of the experiment, it is interesting that the RSVP task detected knowledge through participants' response times once the amount of training was increased. We take this as an indication that the RSVP is, in fact, a less sensitive measure than forced-choice tasks. Furthermore, the fact that the RSVP detected knowledge in this version of the experiment despite its placement after the forced-choice tasks suggests that the order of tasks was not responsible for the failure of the RSVP to detect knowledge in Version 1 of this experiment. In fact, these data indicated that the RSVP has the potential to detect knowledge, provided that a sufficient amount of learning has taken place during exposure. Nevertheless, we found no evidence for a dissociation between our direct measures, the forced-choice tasks, and indirect measure, the RSVP. In other words, our indirect measure of knowledge did not detect any additional information to the forced-choice tasks. As pointed out in our discussion of Version 1 of this experiment, this reinforced our confidence that the measures of conscious knowledge we used this far in this thesis are sensitive enough for the measurement of awareness of knowing.

Performance in the generation task was better than in Version 1 of the experiment, but still poor. Despite the better performance in forced-choice tasks, participants were still unable to recollect the training triplets when asked to do so in the generation task. In this version of the experiment, therefore, we drew the same conclusions regarding the type of knowledge assessed through forced-choice tasks, and suggest that performance in these tasks may rely primarily on strategies such as recognition and familiarity, and may not imply that good performers are also able to reproduce the stimulus material that they have learned.

4.4 Direct and indirect measures in children

We were also interested in comparing visual statistical learning between adults and children using a combination of direct and indirect measures. In particular, similarly to Chapter 2, we aimed to test the hypothesis that the use of implicit and explicit knowledge in visual statistical learning may follow a developmental trajectory, with more implicit knowledge used by children than adults (Daltrozzo & Conway, 2014). Using a very similar methodology to Bertels et al., (2015b), who successfully employed the comparison of direct and indirect measures of knowledge for study with children, we adapted the experiment for use with younger participants by including a 4AFC task and an RSVP task, but no 2AFC task.

4.4.1 Materials and methods

4.4.1.1 Participants

Participants were recruited through the University of Lincoln Summer Scientist event, held annually by the School of Psychology, in which children aged 3 to 10 years and their parents take part in a variety of research studies run by academic staff at the university. In total, 38 participants took part in the experiment: nine participants were 8 years old (6 males and 3 females), 18 participants were 9 years old (4 males and 14 females), and 11 participants were 10 years old (4 males and 7 females). The overall mean age for our sample was 9.05 years (SD = 0.73). One participant had a diagnosis of asthma, but no asthma episode occurred during the testing session. No other participant was registered as having any medical condition or learning differences which could have affected the outcome of the results.

4.4.1.2 Ethics

The study received ethical approval from the School of Psychology Research Ethics Committee (SOPREC) as part of the University of Lincoln Summer Scientist Week, and parental consent was obtained centrally as part of this (see Appendix E.5.1 for ethics application as part of Summer Scientist Week). The researcher provided parents with additional information regarding the experiment, named “Catch the shape” as part of Summer Scientist Week, which contained a written debrief (see Appendix E.5.2 for additional information for parents). Before taking part in the experiment, each individual participant also provided verbal consent, indicating that they wished to play the “Catch the shape” game. Participants were free to withdraw from the study at any point without providing any motivation. At the end of the game, the experimenter explained the purpose of the game.

4.4.1.3 Stimuli

The visual stimuli for this experiment were identical to those of Version 1 in this chapter.

4.4.1.4 Apparatus

Similarly to Chapter 3, the experiment was programmed and run using MATLAB R2017a, and the MATLAB Psychtoolbox (Brainard, 1997; Pelli, 1997; Kleiner et al, 2007). The experiment took place in a quiet room at the University of Lincoln dedicated to the experiment as part of the Summer Scientist event. The experiment program ran on a Samsung laptop with an Intel ® Core ™ i5 processor. The laptop was connected to an HP 24-inch monitor with a resolution of 1921x1080 on which the experiment display and visual stimuli were presented. Participant responses were collected through a Dell keyboard.

4.4.1.5 Procedure

4.4.1.5.1 Exposure phase

The exposure phase was identical to that of Version 1 of the experiment. This is because a shorter exposure length was considered more feasible for an experiment with children, and we aimed to minimise fatigue effects and to maintain the children's attention to the exposure stream. Furthermore, a shorter exposure length was necessary in order for this experiment to fit the requirements of experiments carried out within Summer Scientist Week at the University of Lincoln. To ensure constant attention to the exposure stream, the same cover task was used as in Version 1 of the experiment with the only difference that the cartoon character used as a distractor stimulus was Homer Simpson (Figure 4.17). This was also chosen from Bertels et al., (2015a), who used a range of distractor stimuli, one for each block of their exposure. The reason for this change was that Homer Simpson was considered to be a more popular cartoon character in in the UK than the Marsupilami, and therefore was considered as a more salient distractor for the children in our experiment. Participant instructions were adjusted to be more child-friendly (refer to Appendix E.5.3 for full task instructions).

Figure 4.17: The cartoon character (Homer Simpson) used as visual distractor during the exposure phase. Figure boundaries are only present for the purpose of visual presentation in this thesis. No boundaries were used for visual presentation within the experiment.

4.4.1.5.2 Test phase

4AFC Task

The 4AFC task was identical to that used in Version 1 of the experiment on adults, therefore the shape presentation times were consistent between the exposure stream and this task. However, the conscious status of knowledge was assessed through binary confidence ratings, “guess”, for implicit knowledge, and “remember”, for explicit knowledge, collected after each forced-choice trial. This choice was made for consistency with (Bertels et al., 2015a)’ s use of the guessing criterion with children. Responses were recorded in the same way as in the adult version: on each forced-choice trial, all four shape alternatives were displayed on the bottom half of the screen below the triplet arrangement and labelled 1-4 to indicate participant response keys and “guess” and “remember” knowledge attributions were recorded through pressing keys 1 and 2 on the keyboard, respectively. However, participants did not press any keys on this task, to prevent errors due to accidental key-presses. Instead, participants told their responses to the experimenter, who recorded these through the keyboard.

RSVP Task

The RSVP task was identical to that of Version 1 and Version 2 of the experiment with the exception that instructions were modified to be more child-friendly. Due to the need to record response times in this task, the participants provided the responses themselves through the space bar on the computer keyboard. The researcher monitored and encouraged the participants throughout the experiment, in order to help them maintain their concentration on the tasks. However, no comments were made which might direct them to correct responses in the forced-choice tasks. Overall, the experiment lasted no longer than 15 minutes. Refer to Appendix E.5.3 for full task instructions for all tasks.

Additional measures: questionnaire for parents

The parents of our participants completed a short questionnaire assessing various aspects of the participants' school performance, specifically, their performance in, and enjoyment of, mathematics, English, science, foreign languages and art, as well as their musical sophistication (refer to Appendix E.5.4 for questionnaire). This information was collected based on suggestions by previous correlational studies (Siegelman et al., 2017) that language and mathematical abilities, as well as musical abilities, might correlate with statistical learning. Both academic performance and enjoyment of the different school subjects were assessed on a 10-point Likert scale, where higher scores indicated higher performance/ enjoyment. To assess musical sophistication, we used the perceptual abilities and musical training subscales of the Gold-MSI questionnaire (Müllensiefen et al., 2014).

4.4.2 Results

4.4.2.1 Exposure

In order to discriminate between correct and incorrect response times, we adopted a time window for correct responses and considered all RTs outside of this time window as incorrect. Each shape was presented for 400 msec with a gap of 200 msec before the next shape. Our chosen time window for correct responses went from 150 msec to 600 msec post stimulus. We assumed that any responses falling between stimulus onset and 150 msec post stimulus were too fast to be responses from that stimulus, and therefore were treated as accidental key presses.

Exposure data was only present for 37 participants, out of the 38 total participants who took part in the experiment, because data for one participant's exposure phase was lost due to a technical fault. This participant, however, was highly attentive during this phase of the experiment, therefore his/ her data were retained for subsequent analyses. Similar to Version 1 of the experiment, each participant had to attain a minimum of 60% distractor detection rate for him/her to be included in the analyses. Out of the 37 participants for whom exposure data was available, no participant detected distractors below this threshold, therefore data for all these participants were also retained for analysis. Overall, participants detected an average of 97.5% of distractors in the exposure stream with an average RT of 417.69 msec (SD = 0.05). There were no significant differences in detection rates and response times between age groups. This was taken as an indication of participants' attentiveness to the exposure stream, regardless of age.

4.4.2.2 4AFC task

The mean proportion of correct responses for all ages pooled in the 4AFC task was 0.29 (SD = 0.11), and this was significantly above chance (0.25), $t(37) = 2.369$, p =.011, one-tailed, 95% CIs [-0.013 0.098], Cohen's d = 0.384, suggesting that participants were able to successfully use their knowledge of the triplet structure in this task.

In order to assess any age-related performance differences, we carried out a one-way between-subjects ANOVA with age as the between-subjects factor and 4AFC task performance as the dependent variable. We found no significant main effect of age, $F(2, 35) = 0.643$, $p = .532$, $\eta^2_p = 0.035$. Data for all age groups was pooled for subsequent analyses.

Participants mostly felt that they were guessing in this task: the proportion of "guess" responses was 0.74 ($SD = 0.19$) and the proportion of "remember" responses was only 0.26. ($SD = 0.19$). Performance was at chance (0.25) when participants felt that they were guessing $t(37) = 1.560$, $p = .063$, one-tailed, 95% CIs [-0.027 0.086], Cohen's $d = 0.253$, and significantly above chance when they felt that they remembered, $t(31) = 2.413$, $p = .01$, one-tailed, 95% CIs [0.010 0.226], Cohen's $d = 0.427$, which, based on the guessing criterion, suggests that their knowledge was held explicitly (Figure 4.18). These results indicate that participants were able to learn the statistical structure of the stimuli despite the training phase being shorter than used by previous research (Bertels et al., 2015a).

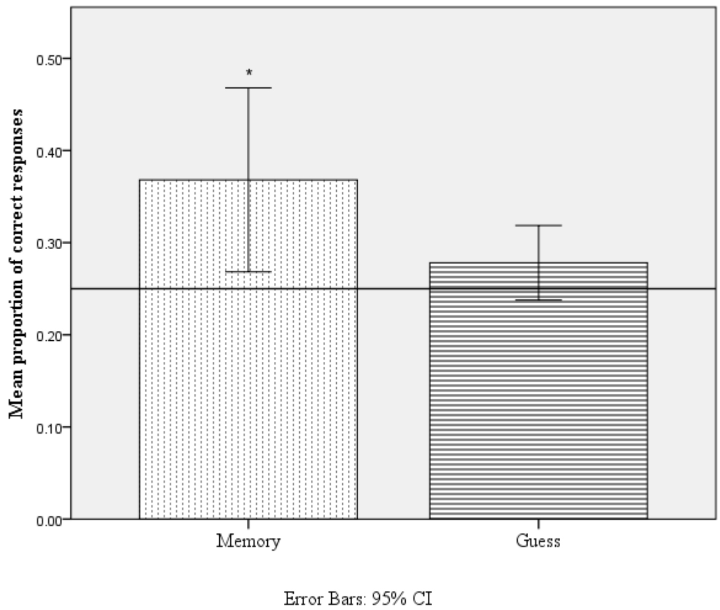

Figure 4.18: Mean proportion of correct responses separately for each type of knowledge attribution (guessing criterion). Line represents chance level (0.25). Conditions in which performance was significantly above chance are marked with one asterisk (*).

4.4.2.3 RSVP task

The same data analysis and data cleaning strategy was adopted for the RSVP in children as for our experiments with adults (Version 1 and Version 2).

Data for only 32 out of 38 participants was present for the RSVP task. Data for 2 participants had to be discarded due to them no longer engaging with the task and pressing the spacebar to each shape presentation on some of the trials. Three participants did not take part in the RSVP task due to excessive fatigue and poor concentration at the end of the 4AFC task.

A comparison of response times to shapes in first (M = 473.1 SE = 7.13), second (M = 493.2 SE = 9.52) and third (M = 481.85 SE = 8.1) position within a triplet found no significant effect of shape position, $F(1.551, 48.085) = 2.755$, $p = .086$, $\eta^2_p = 0.082$. (Greenhouse-Geisser corrected). Similarly, there was no effect of shape position when using the proportion of correct responses as a dependent variable, $F(2,62) = 1.631$, $p = .204$, $\eta^2_p = 0.05$. These results were taken to indicate that the RSVP task did not detect triplet learning in children.

4.4.2.4 Correlations

Questionnaire data was missing for 2 out of 38 participants, due to parents not filling in the questionnaire, therefore data for 36 participants was analysed. We found no significant correlations between the proportion of correct responses in the 4AFC task and any of our other variables of interest.

4.4.3 Discussion

In line with Bertels et al., (2015b), our participants performed above chance in the 4AFC task, indicating that they had acquired knowledge of the statistical structure of the stimuli. The guessing criterion indicated that this knowledge was held explicitly, as participants performed at chance when they were guessing and above chance when they were remembering. Despite the shorter training used in this experiment, compared to Bertels et al., (2015b), our children were still able to perform well in the presence of a distractor task. Similar to the adults (experiment Version 1), the children's knowledge of the triplets was not reflected in response times to shapes in first, second and third position within a triplet in the RSVP task. This could be seen as further reinforcing our argument made previously regarding concerns around the sensitivity of the RSVP task. In fact, our pattern of results in this chapter seems to suggest that a long exposure phase is needed in order to boost learning sufficiently for the RSVP task to detect it through a response-time difference between shape positions.

Our finding of explicit knowledge in children is in line with the results we obtained in Chapter 2 of this thesis regarding auditory statistical learning in these age groups, and backed up by previous research (Weiermann & Meier, 2012; Bertels et al., 2015b). We found no support for the suggestion that implicit knowledge is more prevalent in children than adults (Daltrozzo & Conway, 2014). Counter to a few proposals from previous literature (Vaidya et al., 2007; (Arciuli & Simpson, 2012b; Arciuli & Simpson, 2011), we have also found no evidence that performance, at least in this statistical learning task, follows a developmental trajectory, improving with age. In fact, our comparison of performance for the three age groups was non-significant, failing to reveal any age-related improvement in the task. Our findings of explicit knowledge are also against previous suggestions that children between the ages of 7 and 9 are less able to monitor the correctness of their responses than older children (Koriat & Ackerman, 2010). The uneven sample sizes between these three age groups is a limitation of this experiment, due to the fact that comparisons between the three ages was not our primary aim. It would have been interesting for this study to also include at least one other younger age group, in order to determine the age at which participants become able to perform successfully in this task. In this experiment, we added to the existing knowledge on visual statistical learning in children by confirming its explicitness, and extended this knowledge with our finding that learning in this paradigm is possible after a very short exposure phase.

With regards to the measurement of conscious knowledge through the guessing criterion in children of this age, we suggest that future studies should include intuition as a knowledge attribution, rather than limiting themselves to binary confidence ratings. In the present experiment we had occasional informal reports by our participants that they felt that neither “guess” nor “remember” were an appropriate knowledge attribution rating, as their confidence was “somewhere in between”. We based our choice of binary confidence ratings on previous research which used a similar paradigm to ours (Bertels et al., 2015b). On the basis of the spontaneous verbal reports obtained from our participants in this experiment, we recommend their use in future learning experiments in these age groups. This experiment would have benefitted from a systematic recording of these spontaneous reports by our participants, and a comparison of performance between participants who felt that they were using intuition and the ones who did not.

The same methodological concerns regarding the RSVP task that we discussed previously in relation to our experiments with adults apply to these younger age groups. Similar to adults, children occasionally also commented that they had forgotten which target shape they were required to look for within the shape stream, and we take this as indicative that there could have been more instances of forgotten targets than reported by these participants. We believe that this methodological issue, as well as the length of the task, which we deemed very demanding for our participants in terms of concentration, may be responsible for the failure to replicate the results obtained by (Bertels et al., 2015b). The authors used as much training on their sample of children as we did with adults in Version 2 of the experiment, which would explain why they were successful in obtaining the response-time difference effect in the RSVP. However, it is interesting that they successfully implemented a considerably longer version of the exposure task with children than we have in the present experiment without the results being negatively affected by fatigue effects and poor concentration. This suggests that in future research we may be able to incorporate a longer exposure phase in experiments with younger participants.

In terms of comparing explicit and implicit knowledge between our two age groups, the children in this experiment performed the same 4AFC task as the adults in Version 1 of the study, that is, they were trained with a short exposure phase during which they performed a cover task. Despite the learning effect in the children was smaller than in the adults, the guessing criterion suggested that their knowledge was explicit. Although the children felt that they were guessing in the majority of trials, similar to the adults, their knowledge was at chance in these trials but above chance in trials when they were using memory, in contrast to the adults, whose performance was above chance when they felt that they were guessing. This would suggest that the children in this experiment were better able than the adults to track their knowledge, that is, they were conscious of when they had knowledge, as reflected in above-chance performance when remembering, and when they did not, as reflected in chance performance when guessing. In contrast, our adult participants in Version 1 of this study did not seem equally able to track their knowledge.

There have been proposals that children have a tendency to be over-confident and to over-estimate their knowledge (Fleming & Lau, 2014). This, in combination with the low confidence of our adult participants, could lead to the suggestion that these results are merely caused by excessive confidence in the children. However, it needs to be pointed out that the great majority of knowledge attributions (74%) in children were guesses, which is at odds with the hypothesis that these results were affected by excessive confidence in the children. This, together with the fact that, in those few trials in which they were using memory, the children's responses were indeed correct, suggests that the present findings of explicit knowledge in children are genuine.

Before reaching the conclusion that knowledge in children is more explicit than in adults, two caveats must be borne in mind. Firstly, the adults received the 4AFC task after the 2AFC task, whilst the children received it straight after exposure. Therefore, it is possible that, by the time they got to the 4AFC task, the adults had forgotten some of the knowledge acquired in exposure. Secondly, this study could not directly compare the results of the guessing criterion between the two age groups, as we used binary confidence ratings with children, but three types of knowledge attributions with adults. Given these caveats, and the fact that, given more training, the adults did acquire explicit knowledge in the 4AFC task (study Version 2), we suggest that the conclusion that children's knowledge is more explicit than adults' may not be correct.

Finally, something should be said with regards to the children's performance in the presence of a dual task. The fact that children held explicit knowledge in the presence of a dual task goes against our previous hypothesis that the dual task might have played a role in making knowledge implicit in the 4AFC task in adults (experiment Version 1). Based on the children's data in this experiment, we suggest that explicit knowledge of the statistical regularities can indeed be developed in the presence of a dual task We hypothesise that our measures of conscious knowledge may have indicated implicit knowledge in adults in Version 1 of the experiment potentially due to participants' low confidence in a task which was perceived as difficult. The question of the effects of a dual task on implicit and explicit knowledge is outside the scope of this study. In fact, the primary purpose of our cover task was to maintain participants' attention to the exposure stream. This is nevertheless an interesting topic of investigation and, in order to draw any firmer conclusions, future research should carry out a systematic comparison of dual-task and single-task groups.

4.5 Conclusions

This study focused on the comparison between direct and indirect measures of knowledge in adults and children in the context of a visual statistical learning paradigm (visual triplet learning). It used a two-alternative forced-choice task and a four-alternative forced-choice task as direct measures of knowledge, in combination with the guessing and zero correlation criteria to measure the status of knowledge, and an RSVP task as an indirect measure of knowledge. In order to also assess explicit recollection, we developed a generation task for use in a visual triplet learning paradigm.

With regards to our main question in this study, that is, whether there is a dissociation between direct and indirect tasks, and the related question of the status of knowledge, we found that the RSVP task does not detect any more knowledge than our forced-choice tasks (in our experiment Version 2) and, in fact, sometimes detects less (in our experiment Version 1 and in our experiment with children). We therefore did not find any dissociation between direct and indirect measures of knowledge. As we cannot exclude the possibility that the failure of the RSVP task to detect any knowledge of the triplets may be due to the methodological issue of participants forgetting the target shape, we recommend that, if the use of this task is to be continued, future research should address this methodological challenge. One potential solution could be, for example, to display the target shape on the screen throughout each trial, although this is an option which would need careful piloting, in order to understand, and eliminate potential adverse effects. Based on these results, we concluded that forced-choice tasks alone, in combination with the guessing and zero correlation criterion, provided us with enough information regarding the status of knowledge. Through the application of the guessing and zero correlation criteria, we found that knowledge was prevalently explicit, a result which agrees with our findings in previous chapters of this thesis, with some implicit knowledge in the 4AFC task when a cover task is present and when participants are given a short exposure. We suggest that our measures of consciousness may indicate more implicit knowledge in tasks which are perceived to be more difficult, and in which, consequently, there is low confidence, whilst increased training with the triplet stimuli increases the presence of explicit knowledge.

With regards to age differences in explicit and implicit statistical learning, we found that knowledge in children, as well as in adults, was available for conscious access, a finding which is in line with our previous auditory statistical learning results, indicating that knowledge is explicit in both children and adults. This study, together with the existing literature, suggests that knowledge in children is no more explicit than in adults, and that explicit knowledge in statistical learning does not follow a developmental trajectory.

Through the use of a generation task, this experiment has led to the conclusion that explicit knowledge as measured by awareness tests based on forced-choice tasks, such as the guessing and the zero correlation criteria, and the PDP, does not coincide with a level of recollection in participants that enables them to reproduce the training material. From this, we propose that, in cases when the guessing and zero correlation criteria indicate that our participants hold explicit knowledge, this meta-knowledge, that is, knowledge that participants recognise they have (Fleming & Lau, 2014), must be based on awareness of recognition of the training stimuli, and does not indicate that our participants are able to reproduce the training material when they are not presented with alternatives of already-formed triplets to choose from.

In addition to reinforcing the evidence we have obtained so far in this thesis that the knowledge acquired in statistical learning is mainly explicit, intended as knowledge that participants are aware of having, through this study we suggest that the guessing and zero correlation criteria served us well in detecting all the relevant knowledge held by our participants. In fact, through the use of an RSVP task, we gained confidence that we have not missed any implicit knowledge in our experiments. Therefore, we decided to continue using the guessing and zero correlation criteria in subsequent investigations. The combined use of these measures with the Process Dissociation Procedure (PDP) was not possible in this study, as it would have lengthened the testing sessions excessively. However, we recommend that the PDP is used in combination with subjective measures to counteract the problem of individual bias. For this reason, we decided to re-introduce it in subsequent investigations.

Chapter 5 The effects of presentation speed

5.1 Introduction

The results obtained this far in Chapter 2, Chapter 3 and Chapter 4 of this thesis converged in the suggestion that the knowledge acquired in statistical learning is mostly explicit, as indicated by our measures of recognition, the forced-choice task used in combination with the PDP (Chapter 2 and Chapter 3), as well as the guessing and zero correlation criteria on their own (Chapter 4). Our work in Chapter 4 was aimed at validating these measures by comparing their outcome with an indirect measure of knowledge, the Rapid Serial Visual Presentation (RSVP) task. This was to ensure that no implicit knowledge that may have been present was missed. Despite the methodological challenges posed by the RSVP task, which we discussed at length in Chapter 4, our combination of direct and indirect tasks showed that our measures of knowledge status do not miss any implicit knowledge, a conclusion that we drew based on the absence of a dissociation between the two, direct and indirect, tasks. In fact, the RSVP task detected either less knowledge than our direct, forced-choice measure (Chapter 4, experiment Version 1) or as much knowledge (Chapter 4, experiment Version 2).

The results of Chapter 4 also led to the important conclusion that our forced-choice measures of knowledge, based on recognition, do not provide information regarding participants' ability for explicit recall of the triplet stimuli. This conclusion was arrived at through comparison of the results produced by the guessing and zero correlation criteria, and our generation task. This has implications for research on implicit and explicit knowledge in statistical learning, as it points to the necessity to separate tasks which are based on recognition and tasks which are based on recollection. We argue that tasks based on recollection, such as our generation task, are the only ones that tap into genuinely explicit processes. This distinction will be crucial for future research in this area. Nevertheless, we propose that our combination of measures of conscious knowledge, the PDP and the guessing and zero correlation criteria, not only give us a suitable indication of whether participants are aware of the knowledge they have acquired, but we are also confident, based on our work carried out in Chapter 4, that no implicit knowledge was missed, at least as far as behavioural-only measures allow us to see. Given that we deemed our current measures of conscious knowledge as suitable for the assessment of awareness, which is our chosen operationalisation of "explicit" in this thesis, in this chapter we proceeded to use these measures to investigate the next hypothesis. In fact, based on the existing literature, there is a good reason to believe that speed of stimulus presentation may affect the amounts of implicit and explicit knowledge. We therefore chose to investigate this variable in order to assess whether manipulations of speed could lead to implicit knowledge in statistical learning.

Although research has already compared task performance at different speeds, therefore focusing on the amount of knowledge acquired, we were specifically interested in the question of how speed affects the status of knowledge: implicit or explicit. It could be, for example, that a greater learning effect might also correspond to more explicit knowledge and that, conversely, a smaller learning effect, or weaker knowledge, might correspond to more implicit knowledge. A limited amount of research, particularly investigating motor learning through the SRTT, has previously pointed to the possibility that implicit and explicit knowledge are indeed affected by speed of visual presentation. However, this question has not been systematically investigated in non-motor statistical learning paradigms.

Findings from the motor learning literature, using the STR task, suggest that the type of knowledge acquired may be affected by the speed of stimulus presentation, with more implicit knowledge at faster presentation speeds and more explicit knowledge at slower presentation speeds. Destrebecqz & Cleeremans (2001) manipulated speed in the SRTT through changes in the Response Stimulus Interval (RSI), that is, the interval between the participant's response and the appearance of the next stimulus on the screen. They compared a fast RSI of 0 milliseconds (msec) and a slow RSI of 250 msec. In an assessment of explicit knowledge through the PDP, they found that only participants trained with a longer RSI had been able to perform successfully under exclusion, therefore showing explicit knowledge, whilst participants trained with an RSI of zero had no control over the expression of their knowledge. The findings also suggest that learning is better for a slower than faster task, as in a recognition task participants were only able to distinguish between old and new fragments of the training sequence in the slow speed condition. As this was a motor learning paradigm, it is worth pointing out that response times collected during the training phase showed evidence of motor learning regardless of the speed of the task. These findings led the authors to conclude that the development of explicit knowledge is dependent on how long the participant has to process the stimulus, and therefore to form stronger memory associations between elements. In a similar study, comparing RSIs of 0, 250 or 1500 msec, Cleeremans (2003) assessed explicit knowledge of the motor sequence through verbal reports in the form of a questionnaire which probed the nature of the sequence structure, confidence ratings, a free generation task and a forced-choice recognition test. Despite all participants showed motor learning regardless of the RSI, and all participants reported that they had noticed the presence of a sequence, when awareness was measured through the PDP only participants trained with the slower task speed exhibited control over their knowledge. Specifically, whilst inclusion performance was comparable across all speed conditions, which was taken to indicate that implicit knowledge was present, exclusion performance was only successful at longer RSIs. The presence of explicit knowledge in the slower speed group was also confirmed through the application of the guessing criterion. Miyawaki (2006) proposed that longer RSIs in the SRTT promote explicit knowledge by allowing more time for prediction of the next stimulus and for use of explicit learning strategies. The proposal that, while unconscious knowledge is elicited rapidly, conscious knowledge needs time to form is also present in the Artificial Grammar Learning (AGL) literature (Mealor & Dienes (2012). In the present study we aimed to test this knowledge developed in the context of motor learning, and applied it to two different statistical learning paradigms: transition matrix and triplet learning.

When it comes to non-motor statistical learning, although we have evidence suggesting, in line with the SRTT studies, that performance is better at longer presentation speeds, we do not know whether the amounts of implicit and explicit knowledge used at these different speeds are affected. Arciuli & Simpson (2011) in a triplet learning paradigm where visual triplets were made of cartoon characters, tested three speeds of visual presentation, using a stimulus presentation time of either 200, 400 or 800 msec. Learning was found to improve with slower speeds of presentation, a finding which is consistent with previous data by Turk-Browne et al., (2005), who compared presentation times of 400 and 1000 msec, using visual shapes. These studies were limited to measuring the amount of knowledge acquired through a 2AFC, and neither study investigated changes in implicit and explicit knowledge as a function of speed of visual presentation.

Given suggestions that the effects of speed may be different for vision and audition (Conway & Christiansen, 2009), investigations on the effects of stimulus presentation speed should include a systematic comparison of the visual and auditory modalities. With regards to the auditory modality, to the best of our knowledge, we are not aware of any studies investigating the effects of stimulus presentation speed in a statistical learning paradigm. In an AGL task, Conway and Christiansen (2009) compared the effects of speed of presentation in the visual and auditory modalities. In the visual task, elements of the grammar were implemented as colours, and presented for either 500 or 1000 msec. The auditory task used tones and presented them at two different speeds: 125 msec and 250 msec. The authors found that, whilst learning in the visual modality, as measured by a 2AFC task, was impaired by a faster speed of visual presentation, learning in the auditory modality was not affected by faster presentation rates. This led to the conclusion that vision and audition are differently affected by presentation speed. However, this study did not include a measurement of the type of knowledge acquired, as this was not one of its aims. Within statistical learning, the great majority of research on the speed variable has focused on the visual modality, therefore previous literature does not provide us with an indication as to how speed of presentation affects implicit and explicit knowledge in the auditory modality. In the present study we aimed to address this gap by comparing the visual and auditory modalities, and added to the existing body of knowledge by assessing the effects of speed of stimulus presentation on the type of knowledge acquired.

Furthermore, a speed study was deemed useful for the development of future investigations around the electrophysiological correlates of implicit and implicit knowledge. In fact, establishing an optimal speed for the learning of sequential regularities would be necessary for the purpose of a future EEG study in order to establish an epoch length which would capture the ERP components of interest, whilst at the same time ensuring that learning would be maximal at that given speed of stimulus presentation. In addition to this, for an EEG investigation of implicit and explicit knowledge, it would be useful to first assess behaviourally how these two knowledge types would be affected by speed.

Our work in Chapter 2, Chapter 3 and Chapter 4 of this thesis used a visual stimulus presentation time of 400 msec, and an auditory stimulus presentation time of 200 msec, therefore we took these as our baseline presentation speed for the present study. Our fast and slow presentation speeds were 200 msec faster and slower than the baseline speed, respectively. For our visual statistical learning experiment, these speed conditions also happened to match the visual presentation speeds used by Arciuli & Simpson (2011). Based on the SRTT and statistical learning literature reviewed, we expected to find a larger learning effect at slower than faster stimulus presentations in our visual experiment, and expected the same pattern of findings in the auditory modality. With regards to the status of the acquired knowledge, we expected that knowledge would be more implicit at faster stimulus durations and more explicit at slower stimulus durations.

Given the large individual differences in statistical learning performance that we have observed in previous chapters of this thesis, a secondary aim of this study was to discover whether some of these individual differences are related to certain measures of cognitive performance. For this purpose, we used a reduced version of the Goldsmiths Musical Sophistication Index (Gold-MSI) (Müllensiefen et al., 2014), which includes measures of perceptual ability and musical training. This was based on suggestions that statistical learning may be related to musical ability in different ways (Rohrmeier & Rebuschat, 2012; Kuhn & Dienes, 2005; Kuhn & Dienes, 2006). Furthermore, given previous findings of a correlation between performance in an Artificial Grammar Learning (AGL) task and Digit Span (Misyak & Christiansen, 2012; Karpicke & Pisoni, 2004), we measured our participants' visual and auditory digit span. Previous research has also investigated the relationship between sequential regularities learning and intelligence, mainly failing to find a correlation between the two (Misyak & Christiansen, 2012; Kaufman et al., 2010; Gebauer & Mackintosh, 2007). Aiming to shed light on this relationship, participants' IQ was also assessed in this study.

5.1.1 Auditory statistical learning

5.1.1.1 Materials and methods

5.1.1.1.1 Participants

Seventy-two participants took part in the experiment. Age and gender data was available for 60 participants. There were 45 females (mean age = 20.42, *SD* = 3.82) and 15 males (mean age = 20.13, *SD* = 1.88). Participants were all undergraduate and postgraduate students at the University of Lincoln. All participants except one had English as their first language. Four participants had a diagnosis of dyslexia. All participants had normal or corrected to normal vision and did not have any medical condition which could have affected their participation or the validity of the data. Participants were partly recruited through the University of Lincoln research participation system in exchange for credit points, whilst some participated voluntarily. We randomly allocated participants to one of the three conditions of speed: fast (26 participants), baseline (23 participants) and slow (23 participants).

5.1.1.1.2 Ethics

The study received ethical approval from the University of Lincoln Psychology Research Ethics Committee (see Appendix A for ethical approval form and full details of ethical approval). Participants provided full informed consent and were free to withdraw from the study at any point without providing any motivation, or to withdraw their data at a later point. At the end of the experiment participants were fully debriefed, verbally and in writing (See Appendix F.1 for participant information sheet, consent form and written debrief form).

5.1.1.1.3 Stimuli

The experimental stimuli for this experiment, for both the exposure stream and for the test sequences, were identical to those of our previous auditory transition matrix study, as they were generated from the same deterministic transition matrix (figure 5.1). However, the speed of stimulus presentation was modified to produce three separate sets of stimuli for the three speed conditions. For the fast stimulus presentation condition, tones lasted 100 msec, with an ISI of 20 msec. For the baseline speed condition, tones lasted 200 msec, with an ISI of 20 msec. The choice of baseline speed was made on the basis of our previous auditory experiment using transition matrix. Tones in the slow stimulus presentation condition lasted 400 msec, with an ISI of 20 msec.

		1	2	3	4	5
1	**1**	0	0	0	1	0
1	**2**	0	0	1	0	0
1	**3**	1	0	0	0	0
1	**4**	0	1	0	0	0
1	**5**	0	0	0	0	1
2	**1**	0	0	1	0	0
2	**2**	1	0	0	0	0
2	**3**	0	1	0	0	0
2	**4**	0	0	0	0	1
2	**5**	0	0	0	1	0
3	**1**	1	0	0	0	0
3	**2**	0	1	0	0	0
3	**3**	0	0	0	0	1
3	**4**	0	0	0	1	0
3	**5**	0	0	1	0	0
4	**1**	0	0	0	0	1
4	**2**	0	0	0	1	0
4	**3**	0	0	1	0	0
4	**4**	1	0	0	0	0
4	**5**	0	1	0	0	0
5	**1**	0	1	0	0	0
5	**2**	0	0	0	0	1
5	**3**	0	0	0	1	0
5	**4**	0	0	1	0	0
5	**5**	1	0	0	0	0

Figure 5.1: Deterministic transition matrix used for our three-element and five-element test sequences stimuli, for both the auditory and visual versions. Columns numbered 1-5 (shaded grey) index each possible next element, based on the previous two elements (shaded grey) indicated on each row. Each row/column combination will give the probability that a particular element (1-5) will occur based on the previous two.

5.1.1.1.4 Apparatus

Similarly to Chapter 3 and Chapter 4, the experiment was programmed and run using MATLAB R2017a, and the MATLAB Psychtoolbox (Brainard, 1997; Pelli, 1997; Kleiner et al, 2007). The experiment took place in one of the testing cubicles at the University of Lincoln on an HP computer with an Intel ® Core ™ i5 vPro processor. The experiment display and visual stimuli were presented on an HP 24-inch monitor with a resolution of 1920x1080. Participant responses were collected through a Dell keyboard. The tone stimuli were played in stereo mode through a pair of headphones.

5.1.1.1.5 Procedure

5.1.1.1.6 Exposure phase

The exposure phase was identical to that of our previous auditory transition matrix experiment, except that the total duration of the exposure stream changed depending on experimental conditions, due to the different durations of the tone stimuli. The exposure stream contained 1091 tones. This lasted 2.1 minutes in the fast condition, four minutes in the baseline condition and 7.6 minutes in the slow condition. Prior to starting the experiment, participants were asked to wear the headphones and to set the volume to a comfortable level. In line with our statistical learning paradigm, no mention was made of the statistical regularities in the exposure stream or that there would be a test phase after exposure. We used our previous on-screen instructions: "You will hear a series of tones. Please listen attentively. Press a key to hear the tones."

5.1.1.1.7 Test phase

The 2AFC was administered immediately after the end of exposure. Implementation of the 2AFC and PDP in this experiment was identical to that of our previous auditory transition matrix experiment. There were 50 2AFC trials, each consisting of two test sequences, one structured and one unstructured. There was a total of 25 unique structured sequences, each of which was presented twice during the test, and 50 unique unstructured sequences. The order of presentation of the 50 structured test sequences was randomised per participant such that all 25 structured sequences were presented first, and then a second time. The order of presentation of the 50 unstructured sequences was also randomised per participant.

The two test sequences were presented sequentially and preceded by the on-screen labels “sequence 1” and “sequence 2”, which were displayed for 500 msec before the first and second test sequence, respectively. In half of the 50 forced-choice trials the structured test sequence was presented first and in the other half the unstructured test sequence was presented first. The order of presentation of the structured and unstructured test sequences within each trial was randomised. Each trial was separated by the next trial by a one-second pause.

For the purpose of the PDP, the 2AFC task was administered both under inclusion and exclusion instructions. To counteract any effect of the order of presentation of PDP instructions, half the participants carried out the task under inclusion conditions first and the other half under exclusion conditions first. On-screen inclusion instructions were “Choose which of two sequences sounds MORE FAMILIAR. Press Enter to play the sequences” and exclusion instructions were “Choose which of two sequences sounds LESS FAMILIAR. Press Enter to play the sequences”.

A response was required after both the structured and unstructured sequences had been played using the same keyboard setup as in Chapter 4: participants were required to press the “q” key on the keyboard, labelled “1”, to choose the first sequence that was presented and the “p” key on the keyboard, labelled “2”, to choose the second sequence that was presented. For the purpose of the zero correlation criterion, confidence ratings were collected after each trial using the same 50-100 scale that we used in our previous experiment. Participants responded by typing in a number between 50 and 100. Knowledge attribution ratings for the guessing criterion were “guess”, “intuition” and “memory” and were recorded through pressing number keys 1-3 on the keyboard.

The duration of each test sequence and, consequently, of the test phase depended on the duration of the individual tones in the three different speed conditions.

Refer to Appendix C for standardised verbal instructions

5.1.1.1.8 Additional measures: musical sophistication, IQ and working memory

Based on previous correlational studies in statistical learning (Siegelman et al., 2017), and with the aim to detect factors outside of our task which might be responsible for the variation in performance between participants, the perceptual abilities and musical training subscales of the Gold-MSI questionnaire (Müllensiefen et al., 2014) were administered at the beginning of the testing session (Appendix F.3). At the end of the testing session, we administered the National Adult Reading Test (NART) (Bright, Jaldow, & Kopelman, 2002) as a substitute for a measure of participants' IQ (Appendix F.4), as well as an auditory and visual digit span task.

Overall, the experiment took no longer than 60 minutes.

5.1.1.2 Results

Data for three participants in the slow condition was lost due to corruption of the Matlab data files, which could not be recovered. Therefore, data for 20 participants was analysed in the slow condition, 23 participants in the baseline speed condition and 26 participants in the fast speed condition.

Process Dissociation Procedure

For the purpose of the PDP, 2AFC task performance was analysed under inclusion and exclusion instructions. In the fast presentation speed group, the proportion of training sequences chosen (M = 0.53, SD = 0.08) was significantly above chance (chance level = 0.5) under inclusion conditions, $t(25)$ = 2.229, p = .018, one-tailed, 95% CIs [-0.017 0.083], Cohen's d = 0.437, but at chance under exclusion conditions (M = 0.48, SD = 0.10), $t(25)$ = -

1.077, p = .292, two-tailed, 95% CIs [-0.081 0.038], Cohen's d = 0.211, suggesting that, although participants acquired knowledge that they could use in the 2AFC when asked which of two sequences sounded more familiar, they had no control over the use of this knowledge in this speed condition. This was confirmed by a paired-samples t-test, showing that there was no significant difference in the proportion of training sequences chosen under inclusion and exclusion instructions, $t(25) = 1.929$, $p = .065$, 95% CIs of the difference [-.004 .113], Cohen's d = 0.378.

In the baseline presentation speed group, the proportion of training sequences chosen (M = 0.73, SD = 0.11) was significantly above chance (0.5) under inclusion conditions, $t(22)$ = 10.441, $p < .001$, one-tailed, 95% CIs [0.170 0.297], Cohen's d = 2.177, and significantly below chance under exclusion conditions (M = 0.28, SD = 0.12), $t(22)$ = -9.07, $p < .001$, two-tailed, 95% CIs [-0.292 -0.157], Cohen's d = -1.891, indicating that participants had control over the expression of their knowledge and could conform to exclusion instructions. The proportion of training sequences chosen was significantly higher under inclusion than under exclusion instructions, $t(22)$ = 10.683, $p < .001$, two-tailed, 95% CIs of the difference [0.369 0.547], Cohen's d = 2.228. In order to further investigate whether or not the level of control was the same in exclusion or inclusion, that is, whether there was any implicit knowledge at all in this condition, we also compared the proportion of structured sequences chosen under inclusion (M = 0.73, SD = 0.12) to the proportion of unstructured sequences chosen under exclusion (M = 0.72, SD = 0.12) in a paired-samples t-test. The result was non-significant, $t(22)$ = 0.486, p = .632, two-tailed, 95% Cis of the difference [-0.031 0.050], Cohen's d = 0.101, again, showing that participants were able to conform to exclusion instructions, and therefore that their knowledge was explicit.

Similarly, participants in the slow presentation speed group chose training sequences significantly above chance under inclusion (M = 0.85, SD = 0.12), $t(19)$ = 14.709, $p < .001$, one-tailed, 95% CIs [0.293 0.417], Cohen's d = 3.289, and significantly below chance under exclusion (M = 0.16, SD = 0.10), $t(19)$ = -15.548, $p < .001$, two-tailed, 95% CIs [-0.404 -0.278], Cohen's d = -3.477, again, indicating that they had control over the expression of their knowledge. A significantly larger proportion of training sequences was chosen under inclusion instructions than under exclusion instructions, $t(19) = 16.364$, $p < .001$, 95% CIs of the difference [0.603 0.781], Cohen's $d = 3.659$. Similarly to the baseline condition, we also carried out a paired-samples t-test between the proportion of structured sequences chosen under inclusion ($M = 0.85$, $SD = 0.12$) and the proportion of unstructured sequences chosen under exclusion ($M = 0.84$, $SD = 0.10$). The result was non-significant, $t(19) =$, $p = .578$, two-tailed, 95% Cis of the difference [-0.027 0.047], Cohen's $d = 0.127$, indicating that participants' knowledge was explicit.

Refer to Table 5.1 for descriptive statistics and to Figure 5.2 for a summary of 2AFC task performance under inclusion and exclusion instructions for the three speed groups For the purpose of the PDP, Figure 5.2 represents the mean proportion of training sequences chosen as a dependent variable.

Speed condition	**PDP instructions**	**Mean (SD)**
Fast	Inclusion	0.53 (0.08)
	Exclusion	0.48 (0.10)
Baseline	Inclusion	0.73 (0.12)
	Exclusion	0.28 (0.12)
Slow	Inclusion	0.85 (0.12)
	Exclusion	0.16 (0.10)

Table 5.1: Descriptive statistics for the proportion of training sequences chosen under inclusion and exclusion instructions (PDP) separately for the three different conditions of speed.

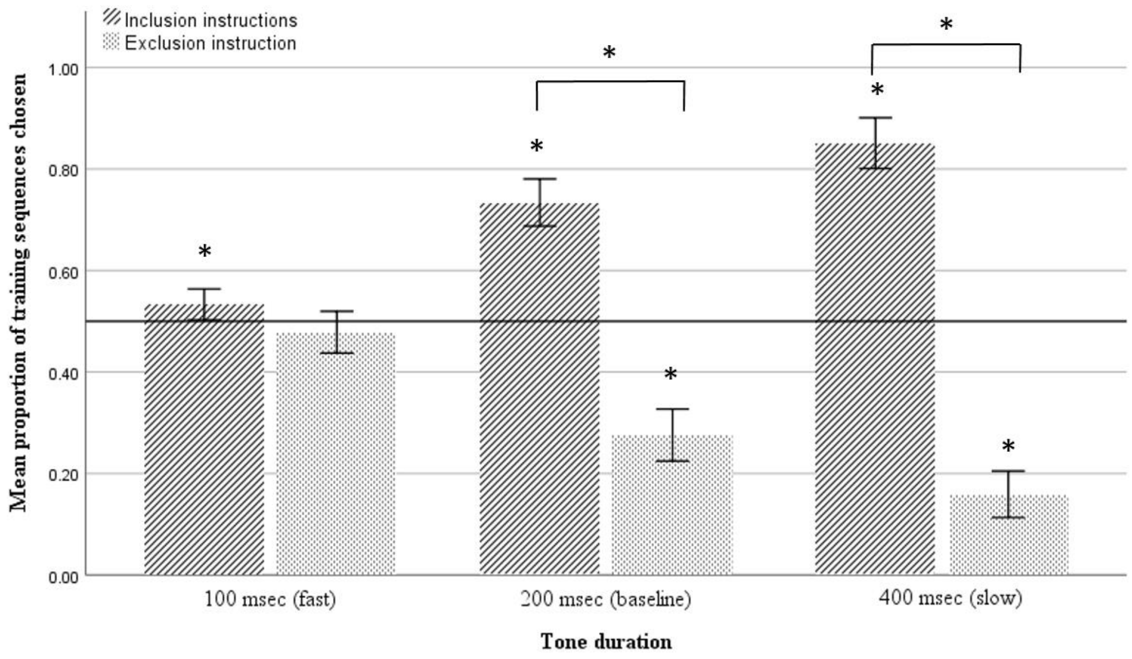

Figure 5.2: Mean proportion of training sequences chosen under inclusion and exclusion instructions (PDP) separately for three different conditions of speed. Error bars represent 95% confidence intervals. Line represents chance level in the 2AFC (0.5). Conditions in which performance significantly differed from chance, as well as significant differences between pairs of conditions, are marked with an asterisk (*).

Guessing and zero correlation criteria

Overall, in the fast condition the majority of knowledge attributions used were intuition, and in the baseline and slow condition mostly memory attributions were used. This was true of both inclusion and exclusion instructions, indicating that a slower stimulus presentation speed benefitted participants' memory under both conditions. This is represented in Figures 5.3 and 5.4 which show the proportion out of the total 2AFC trials in which each of the different knowledge attributions was used.

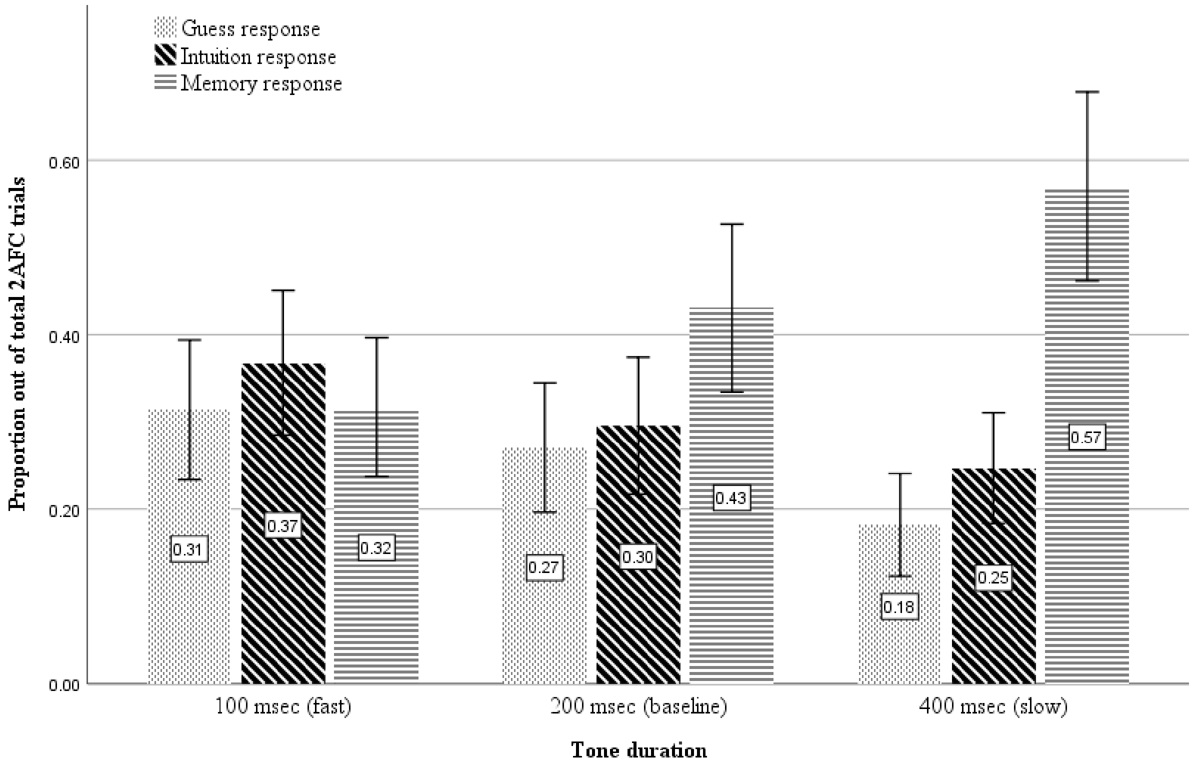

Figure 5.3: Proportion of 2AFC trials out of total in which guess, intuition and memory attributions were used, separately for each condition of speed under inclusion instructions. Error bars represent 95% confidence intervals.

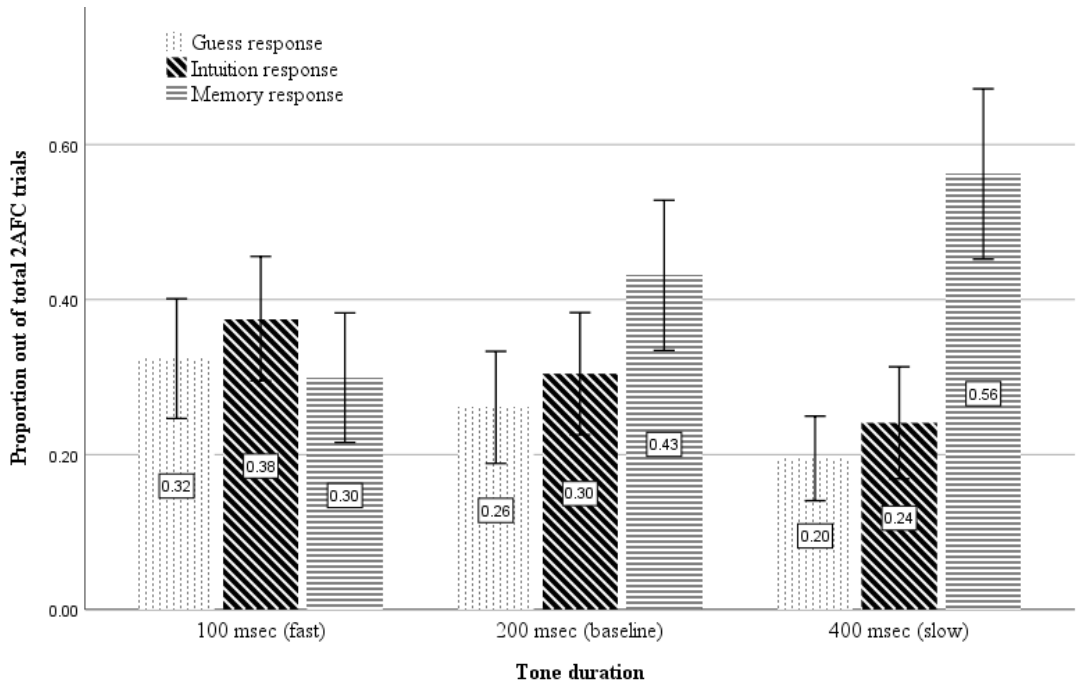

Figure 5.4: Proportion of 2AFC trials out of total in which guess, intuition and memory attributions were used, separately for each condition of speed under exclusion instructions. Error bars represent 95% confidence intervals.

For the purpose of the guessing criterion, the proportion of correct responses in trials where participants were guessing, using their intuition or their memory was compared separately to chance (0.5). This analysis was carried out for both inclusion and exclusion instructions. Results of the one-sample t-tests are displayed in Table 5.2.

			N	Mean (SD)	*t*	df	*P*	Cohen's *d*
Fast (100 msec)	**Inclusion**	**Guess**	23	0.46 (0.11)	-1.558	22	.067	-0.325
		Intuition	26	0.53 (0.14)	1.136	25	.134	0.223
		Memory	25	0.53 (0.21)	.691	24	.248	0.138
	Exclusion	**Guess**	24	0.43 (0.20)	-1.598	23	.124	-0.326
		Intuition	25	0.53 (0.17)	.750	24	.461	0.150
		Memory	25	0.60 (0.19)	2.619	24	.015*	0.524
Baseline (200 msec)	**Inclusion**	**Guess**	23	0.57 (0.25)	1.335	22	.098	0.278
		Intuition	21	0.67 (0.20)	3.790	20	.002*	0.827
		Memory	23	0.83 (0.14)	11.050	22	>.001**	2.304
	Exclusion	**Guess**	23	0.57 (0.17)	1.857	22	.077	0.387
		Intuition	21	0.69 (0.13)	6.895	20	>.001**	1.505
		Memory	23	0.81 (0.14)	10.403	22	>.001**	2.169
Slow (400 msec)	**Inclusion**	**Guess**	19	0.70 (0.25)	3.461	18	.001**	0.794
		Intuition	18	0.79 (0.20)	6.464	17	>.001**	1.524
		Memory	20	0.93 (0.08)	25.183	19	>.001**	5.631
	Exclusion	**Guess**	19	0.56 (0.24)	1.119	18	.278	0.257
		Intuition	19	0.83 (0.15)	9.349	18	>.001**	2.145
		Memory	20	0.93 (0.08)	23.470	19	>.001**	5.248

Table 5.2: One-sample t-tests comparing the proportion of correct responses for each of the three knowledge attributions to chance level (0.5) – guessing criterion. Results are displayed separately for inclusion and exclusion conditions and for condition of speed. Significant p-values are marked with one asterisk (*) for significance at the 0.05 level and two asterisks (**) for significance at the 0.01 level. Results for inclusion are one-tailed.

A visual representation of the guessing criterion for inclusion and exclusion instructions can be found in Figures 5.5 and 5.6, respectively. For the purpose of representing the guessing criterion, these figures depict the mean proportion of correct responses as a dependent variable.

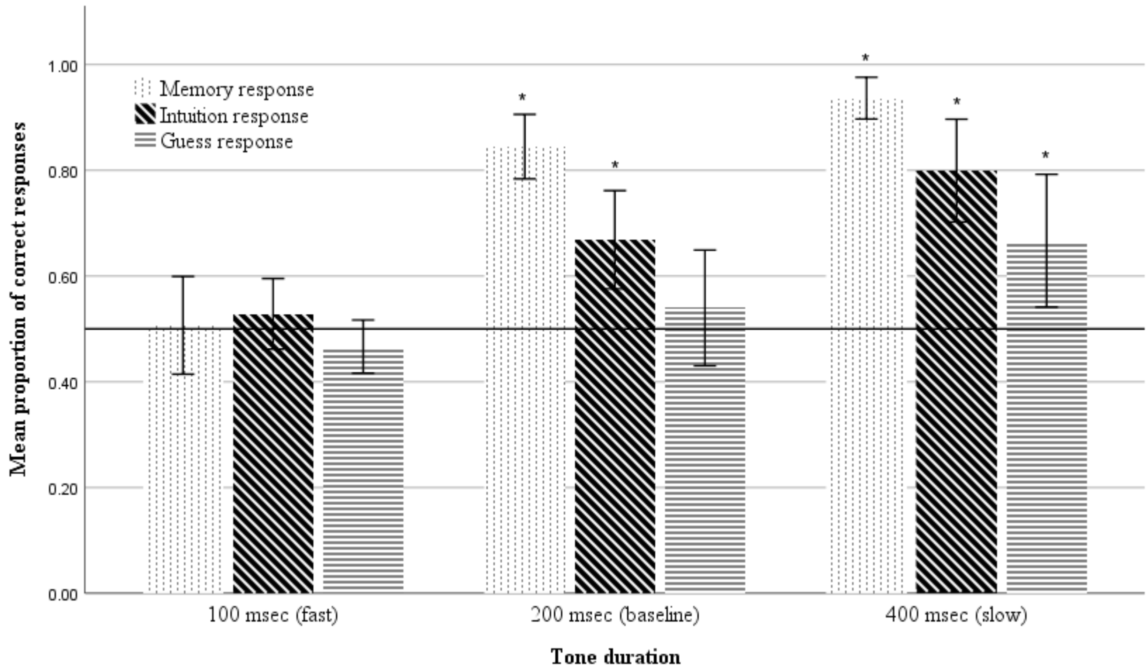

Figure 5.5: Mean proportion of correct responses in the 2AFC task separately for each type of knowledge attribution (guessing criterion) under inclusion instructions. Line represents chance level (0.5). Conditions in which performance was significantly different from chance are marked with one asterisk (*). Error bars represent 95% confidence intervals.

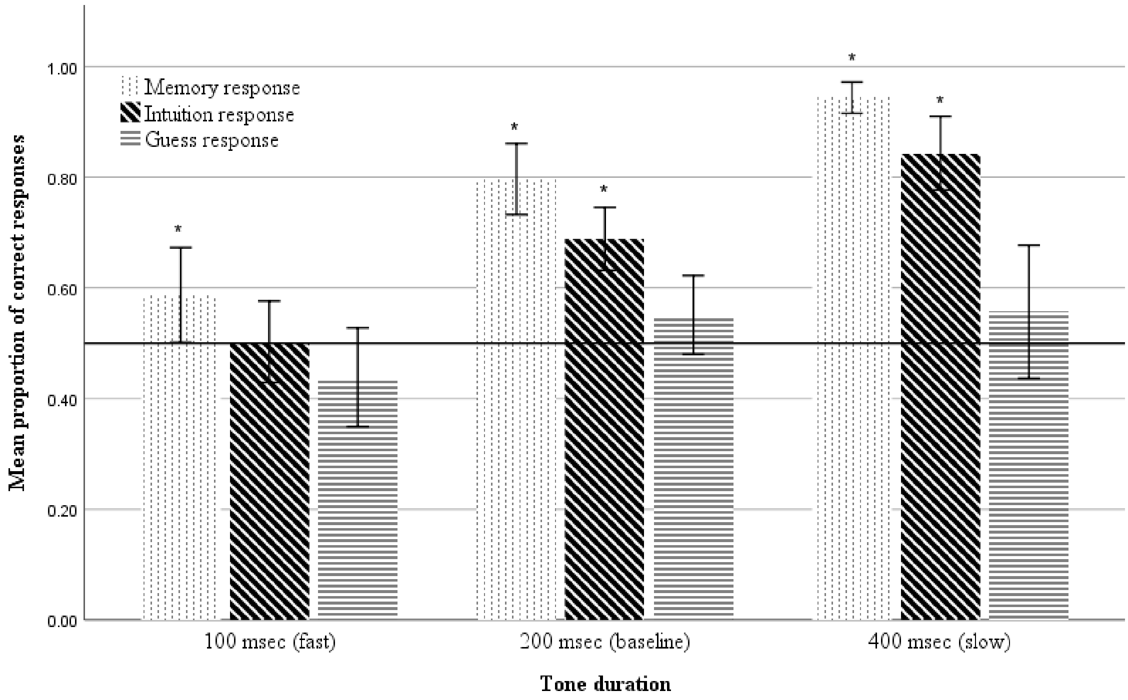

Figure 5.6: Mean proportion of correct responses in the 2AFC task separately for each type of knowledge attribution (guessing criterion) under exclusion instructions. Line represents chance level (0.5). Conditions in which performance was significantly different from chance are marked with one asterisk (*). Error bars represent 59% confidence intervals. Note that the proportion of correct responses under exclusion is the proportion of "new", or untrained, sequences chosen.

For the purpose of the zero correlation criterion, a paired-samples t-test was carried out between confidence in trials where participants were correct and in trials when they were wrong. As can be seen in Table 5.3, confidence was significantly higher when correct than when wrong in all conditions of speed and for both inclusion and exclusion instructions and, furthermore, the confidence difference between correct and incorrect responses increased as the speed of the tones became slower. By the guessing criterion, this indicates that participants' knowledge was explicit and that participants were more confident about their judgements on slower stimuli.

Speed	PDP condition	Response correctness	*N*	Mean (SD)	*t*	df	*p*	Cohen's *d*	95% Cis of the difference
Fast (100 msec)	**Inclusion**	**Correct**	26	67.62 (8.85)	4.859	25	>.001**	0.953	[1.442 3.563]
		Incorrect	26	65.12 (8.00)					
	Exclusion	**Correct**	26	65.94 (8.38)	2.539	25	.018*	0.498	[0.307 2.944]
		Incorrect	26	64.32 (8.44)					
Baseline (200 msec)	**Inclusion**	**Correct**	23	71.13 (7.92)	4.897	22	>.001**	1.021	[4.446 10.980]
		Incorrect	23	63.42 (5.39)					
	Exclusion	**Correct**	23	70.79 (8.27)	4.183	22	>.001**	0.872	[3.464 10.276]
		Incorrect	23	63.92 (8.11)					
Slow (400 msec)	**Inclusion**	**Correct**	18	75.97 (9.07)	3.983	17	.001**	0.939	[6.714 21.837]
		Incorrect	18	61.70 (10.92)					
	Exclusion	**Correct**	20	76.80 (9.58)	6.955	19	>.001**	1.555	[11.507 21.415]
		Incorrect	20	60.34 (8.07)					

Table 5.3: Results of paired-samples t-tests comparing confidence in trials when participants were correct and when they were incorrect (guessing criterion). Results are displayed separately for inclusion and exclusion conditions and for speed condition. Significant p-values are marked with one asterisk (*) for significance at the 0.05 level and two asterisks (**) for significance at the 0.01 level.

Correlational analyses

As we were interested in the correlation between auditory statistical learning and other abilities regardless of speed, correlational analyses were carried out on the data pooled across speed conditions. As shown in Table 5.4 there was a significant positive correlation between the proportion of correct responses under inclusion and the perceptual abilities subscale of the Gold-MSI. However, exclusion performance did not correlate with either of the musical sophistication dimensions. Neither inclusion performance nor exclusion performance correlated with NART scores, auditory digit span or visual digit span, although, interestingly, there was a significant positive correlation between musical training and NART scores and between visual digit span and perceptual abilities.

		1	2	3	4	5	6	7
1 Auditory DSpan	***r***							
	p							
	N							
2 Visual DSpan	***r***	.220						
	p	.091						
	N	60						
3 NART score	***r***	.158	.246					
	p	.243	.065					
	N	56	57					
4 Perceptual abilities	***r***	.162	$.287^{*}$	.235				
	p	.246	.043	.103				
	N	53	50	49				
5 Musical training	***r***	.132	.270	$.496^{**}$	$.533^{**}$			
	p	.340	.056	.000	.000			
	N	54	51	50	58			
6 Inclusion performance	***r***	-.142	.115	-.248	$.288^{*}$	-.004		
	p	.263	.378	.059	.028	.977		
	N	64	61	59	58	59		
7 Exclusion performance	***r***	-.059	.202	-.245	.223	.030	$.831^{**}$	
	p	.642	.119	.061	.093	.822	.000	
	N	64	61	59	58	59	69	

Table 5.4: Correlation matrix illustrating the relationship between the proportion of correct responses under inclusion and exclusion conditions and our oher variables of interest. Correlations significant at the 0.05 level (two-tailed) are marked with one asterisk (*) and correlations significant at the 0.01 level (two-tailed) are marked with two asterisks (**).

5.1.1.3 Discussion

In this experiment we tested implicit and explicit knowledge in auditory statistical learning with stimuli generated through a transition matrix. In order to assess whether auditory presentation speed affects the status of knowledge acquired in this paradigm (implicit or explicit) we used the Process Dissociation Procedure (PDP) in combination with the guessing and zero correlation criteria. The PDP provided some evidence for implicit knowledge in the fast group, through the lack of a significant difference between the proportion of training sequences chosen under inclusion and exclusion, as well as the above-chance performance under inclusion but at-chance performance under exclusion. It is important to bear in mind, however, that this implicit knowledge result was weak and fairly marginal, as performance under both conditions was close to chance. It should therefore be interpreted with caution.

The PDP also showed that participants had control of their knowledge in the baseline and slow groups. Under inclusion, the guessing criterion showed not enough knowledge to analyse in the fast condition, explicit knowledge in the baseline condition, and both implicit and explicit knowledge in the slow condition. Under exclusion, it showed some explicit knowledge in the fast condition, explicit knowledge in the baseline condition and also in the slow condition. The zero correlation criterion showed that participants' confidence was significantly higher when they were correct than when they were incorrect, which the literature interprets as explicit knowledge (Zoltán Dienes, 2004; Ziori & Dienes, 2006), in all conditions of speed. We therefore obtained a picture of mostly explicit knowledge in this experiment, with some implicit knowledge in the fast stimulus presentation condition, and also encountered some contradictions between our three methods used to measure the status of knowledge.

The slow speed of auditory presentation was a demonstration of how the PDP and guessing criteria worked together. The application of the guessing criterion to the exclusion condition of the PDP is, to the best of our knowledge, a new use, which could shed more light on the relative contribution of implicit and explicit knowledge. The PDP indicated that knowledge was conscious in this speed condition, seen by a significantly higher proportion of training sequences chosen under inclusion than exclusion, and by the choice of training sequences significantly below chance under exclusion. Inclusion performance could be driven by both implicit and explicit knowledge (Wilkinson & Shanks, 2004a). When we isolated inclusion trials in which participants were guessing, using their intuition or their memory, some unconscious knowledge emerged. In fact, in trials in which participants were guessing, which were only 18% of the inclusion trials in this condition, they still performed significantly above chance. Successful exclusion performance, on the other hand, is thought to only rely on explicit knowledge. This was confirmed by our application of the guessing criterion to the exclusion condition, which showed that, when participants thought that they were guessing, they indeed performed at chance, whilst, when they were using their intuition, they performed significantly above chance. Overall, the results pointed to less implicit knowledge in the slow condition compared to the others.

The results of the PDP and the guessing criterion appeared to be in contradiction when looking at exclusion performance in the fast tone presentation speed. Looking at exclusion performance, this showed that knowledge was implicit, as participants could not control it: their choice of training triplets was, on average, at chance. However, when isolating those trials in which participants were remembering, which was on 30% of the trials, the proportion of correct responses, intended as the proportion of "new", untrained sequences chosen, was significantly above chance. Chance performance when guessing, reinforced by above-chance performance when using memory, could be interpreted as explicit knowledge according to the guessing criterion. We took this discrepancy between these two measures of conscious knowledge to indicate that, in the fast condition, participants had unconscious knowledge, meaning that they had no control over their knowledge. However, there were trials, specifically, 30% of the exclusion trials, in which explicit knowledge, intended as awareness of knowing, or, in our specific case of the memory attribution, awareness of remembering, was present. We took this as evidence of mostly unconscious knowledge, with some explicit knowledge. Based on these findings, we suggest that our application of the guessing criterion in combination with the PDP is helpful in this field of research to better understand the relative contribution of implicit and explicit knowledge. In fact, when applied to our data, it was helpful in the discovery of explicit knowledge in a context in which knowledge appeared to be entirely implicit.

It is also worth noting that, despite performance was overall above chance under inclusion when we assessed conscious knowledge using the PDP, when assessing whether performance was above chance separately for guessing, intuition and memory for the purpose of the guessing criterion, none of the three one-sample t-tests was significant. We suggest that this contradiction could be due to the way that the data was analysed for the guessing criterion: the analysis isolates trials in which participants were using each of the three types of knowledge attributions, therefore each per-participant average might come from only a small number of trials, thus resulting in a statistical analysis with low power. For example, in our slow stimulus presentation group, under inclusion conditions, only 18% of trials were guesses whilst 57% of trials were memory responses. The unbalanced statistical power between analyses of guessing, intuition and memory attributions is something to be aware of when interpreting the results of our one sample t-test and a methodological concern around the guessing criterion which future studies should be aware of.

Overall, these data indicated that, although learning was present for all our three speed groups, 200 msec is the optimal tone duration for explicit knowledge in the auditory modality. In fact, our results suggested that there is implicit knowledge in the fast stimulus presentation, and we could rule out the presence of some implicit knowledge in the slow presentation speed group. In contrast, all our three measures of conscious knowledge suggested that this was explicit in the baseline presentation speed group. Therefore, on the basis of these data, we were led to the conclusion that, in auditory statistical learning, a tone presentation of 200 msec maximises explicit knowledge.

The results of the PDP seemed to support the idea that knowledge is more explicit at slower stimulus durations. In fact, our fast stimulus duration was the only condition in which participants did not have control over their knowledge. These findings are in line with theories developed within motor statistical learning, using the SRTT paradigm, that a faster stimulus presentation coincides with more implicit knowledge and that knowledge at faster stimulus presentations is based on weaker representations (Destrebecqz & Cleeremans, 2001;

Cleeremans, 2003). In our data, we suggest that this was evident in the smaller effect size of the learning effect that we observed in the fast stimulus presentation group. Furthermore, the fact that more memory attributions were used in the baseline and slow speed conditions suggests an increase in confidence, with is also consistent with the proposal that slower stimulus durations generate stronger representation, and knowledge that is more explicit. In line with previous authors (Mealor & Dienes, 2012), it appears that, at slower stimulus presentation speeds, participants have more time to use explicit strategies, and to form relationships between elements within the auditory sequences. Based on these parallels between our data and previous investigations, we suggest that the effects of speed on non-motor auditory statistical learning tested with a transition matrix paradigm can be explained using the same theories available in the literature which apply to motor statistical learning.

Our significant correlation between the perceptual abilities subscale of the Gold-MSI and the proportion of correct responses under inclusion instructions might be suggestive of a specific relationship between auditory statistical learning and perceptual abilities, given that there was no correlation between 2AFC task performance under inclusion and musical training. Interestingly, the correlation between the proportion of correct responses under exclusion instructions and perceptual abilities did not reach significance. The missing data in our correlational analysis was a limitation in this experiment, and we cannot entirely rule out that, if a larger sample size was used, some of our correlations which, in the present data, approached statistical significance may become significant. Nevertheless, we suggest that this result could be explained by differences in the cognitive processes required for inclusion and exclusion performance in the PDP. Specifically, we propose that, as successful exclusion requires a combination of the perceptual skills required for inclusion, but also an additional top-down control element, it is still related to perceptual skills in music, but less strongly than inclusion performance and, for this reason, we did not observe a significant correlation in these data. This explanation appears to fit well with our patter of correlation results.

We obtained a significant correlation between NART scores and musical training. This is a result which, in our view, leads to concerns around the appropriateness of the NART test for the purpose of this experiment. We chose the NART test as a correlational measure in this study due to its suitability in estimating premorbid intelligence (Bright et al., 2002), and because it can be rapidly administered, which we deemed important to avoid lengthening an already long testing session, therefore risking to negatively impact participant performance.

The NART test consisted of words which have an irregular correspondence between graphemes and phonemes in the English vocabulary, such as “gaoled”, “syncope” or “demesne” (refer to Appendix F.4). We hypothesise that participants who were exposed to wider reading through their upbringing, which might be more likely within a higher socio-economic background, are more likely to have encountered these words and, as part of this kind of upbringing, may also be more likely to have received musical training. We therefore propose that the correlation between participants’ NART scores and their level of musical training could be explained by variables relating to their socio-economic background. As the vast majority of our participants were undergraduate university students, we did not have access to a varied enough participant pool to be able to analyse the effects of this variable. Although level of education and employment status data were collected for our participants, our sample was too uniform with respect to these variables for us to be able to meaningfully include them in our statistical analyses.

This hypothesised relationship between NART scores and our participants’ upbringing highlights the possibility that the NART test did not tap into the IQ of our participants, which might explain the lack of a correlation with auditory statistical learning in this experiment. In this respect, our data went against the suggestion that the NART test does not perform differently, and, in fact, performs better, than demographic variables in estimating IQ (Bright et al., 2002). Given the results of this experiment, we were unable to draw any firm conclusions regarding the relationship between IQ and auditory statistical learning, and decided that in future studies we would select a test of IQ which is less dependent on the demographic characteristics of our participant.

Given the existing evidence of a correlation between Digit Span and performance in AGL tasks (Misyak & Christiansen, 2012; Karpicke & Pisoni, 2004), our results were surprising, as there was no evidence in our data of a relationship between auditory statistical learning and either auditory or visual digit span. We did find a significant correlation between visual Digit Span and the perceptual abilities subscales of the Gold-MSI, which is a surprising effect. It may be interesting for future research to attempt to discover which underlying variables may be responsible for this observed relationship. However, with regards to auditory statistical learning and Digit Span, we were unable to draw any conclusions based on these data.

5.1.2 Visual statistical learning

We subsequently set out to investigate the effects of speed of visual presentation on implicit and explicit knowledge in visual statistical learning.

5.1.2.1 Materials and methods

5.1.2.1.1 Participants

Eighty-two participants took part in the experiment. Demographics were missing for one participant due to him/ her not answering the demographics section of the questionnaire. Of the remaining participants, there were 62 females (mean age = 20.53 *SD* = 5.41) and 19 males (mean age = 20.37 *SD* = 1.71). All participants were undergraduate and postgraduate students at the University of Lincoln and either participated voluntarily or were recruited through the University of Lincoln research participation system, through which they received credit points in exchange for participation. Seventy-five participants had English as their first language, three were native Polish speakers, two were native Sri Lankan speakers, and one was a native Chinese speaker. Four participants had a diagnosis of dyslexia. All participants had normal or corrected to normal vision and did not have any medical condition which could have affected their participation or the validity of the data. Participants were randomly allocated to one of three conditions of speed: fast (27 participants), baseline (27 participants) and slow (28 participants).

5.1.2.1.2 Ethics

The study received ethical approval from the University of Lincoln Psychology Research Ethics Committee (see Appendix A for ethical approval form and full details of ethical approval). Participants provided full informed consent and were free to withdraw from the study at any point without providing any motivation, or to withdraw their data at a later point. At the end of the experiment participants were fully debriefed, verbally and in writing (See Appendix F.2 for participant information sheet, consent form and written debrief form).

5.1.2.1.3 Stimuli

The L1 and L2 triplets for this experiment were identical to those used in Chapter 4 of this thesis (Figure 5.7). The visual presentation speed was modified to produce three separate sets of stimuli for the three conditions of speed. Shapes were displayed on the screen for 200 msec in the fast condition, 400 msec in the baseline condition and 800 msec in the slow condition. The ISI was 200 msec in all speed conditions. The speed for the baseline condition was determined on the basis of our previous visual triplet learning study.

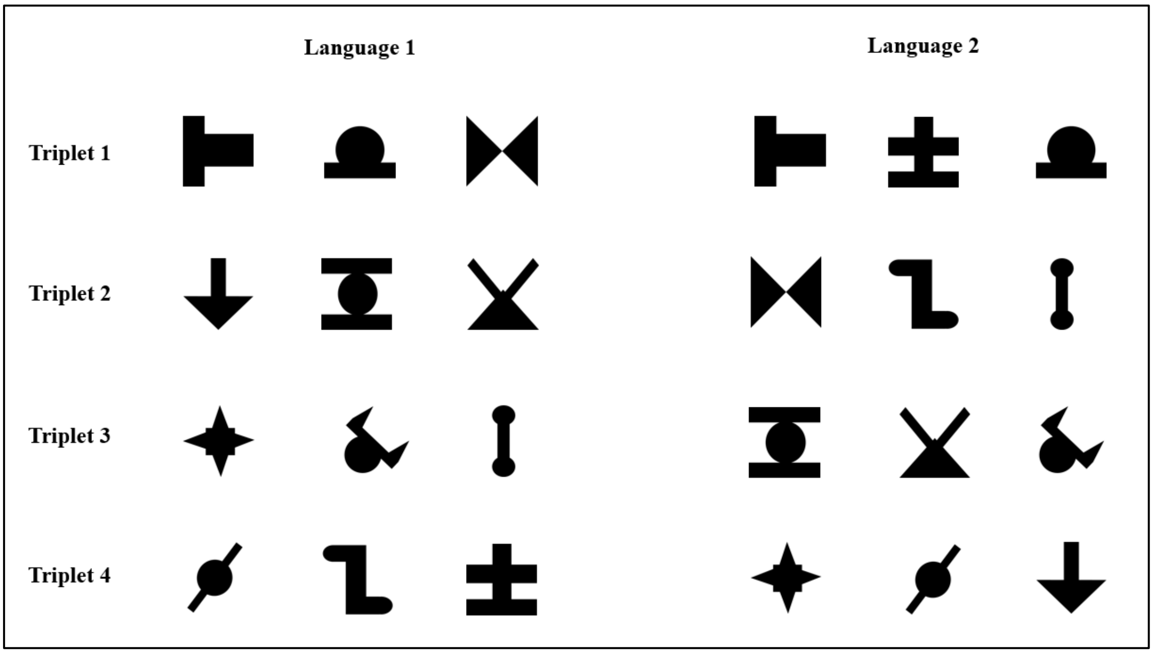

Figure 5.7: Shape triplets for Language 1 and Language 2.

5.1.2.1.4 Apparatus

The apparatus used for the visual version of the experiment is identical to that of the auditory version in this chapter, with the exception that no headphones were needed.

5.1.2.1.5 Procedure

The procedure for this experiment was very similar to that of our previous visual triplet learning experiment (Chapter 4).

5.1.2.1.6 Exposure phase

This experiment used the same symbolic exposure stream as the one used in Chapter 4. The exposure stream was made up of 96 triplets, therefore 288 shapes. Each of the four triplets appeared 24 times during exposure. The L1 exposure stream was formed using the L1 triplets and the L2 exposure stream was formed using the L2 triplets. Half of our participants were trained on the L1 stream and the other half were trained on the L2 stream. The shapes were presented sequentially on the screen and were black against a white background. The presentation times, and therefore the overall duration of the exposure stream, changed depending on the specific speed condition. The exposure stream was just under two minutes for the fast condition, just under three minutes for the baseline condition and just under five minutes for the slow condition. The instructions were equivalent to those of our previous experiments: “You will see a series of shapes. Please watch attentively. Press a key to see the shapes”. No mention was made of the statistical regularities in the exposure stream or that there would be a test phase afterwards.

5.1.2.1.7 Test phase

The implementation of the 2AFC task was very similar to that of our previous visual triplet learning experiment. There were 32 2AFC trials, each consisting of a triplet from L1 and a triplet from L2, the order of which was counter-balanced. The 32 2AFC test trials encompassed all possible combinations of triplets from each of the two languages and contained 8 repetitions of each of the four triplets from L1 and L2. The order of test trials was randomised per participant. Each 2AFC trial presented the two visual shape triplets sequentially, shape by shape, and at the same pace as during exposure, which was either at a fast, baseline or slow speed, depending on the speed condition. Each triplet was preceded by the labels “sequence 1” and “sequence 2” displayed for 500 msec before the first and second visual triplet, respectively. The end of the first test triplet and the presentation of the “sequence 2” label were separated by a 500-msec pause. Trials were separated by a 1-second pause.

To assess the conscious status of knowledge through PDP, the 2AFC task was administered under inclusion and exclusion conditions. The order of these was counter-balanced. On-screen instructions were “Choose which of two sequences sounds MORE FAMILIAR. Press Enter to play the sequences” and exclusion instructions were “Choose which of two sequences sounds LESS FAMILIAR. Press Enter to play the sequences”. After both the triplet from L1 and from

L2 had been presented, a response was required. In the same way as for the auditory experiment, keys were changed to the "q" key on the keyboard to choose the 1st sequence that was presented, labelled "1" using a keyboard sticker, and to the "p" key to choose the second sequence that was presented, labelled "2" using a keyboard sticker. Participants responded using separate hands, their left index finger for the "q" key and their right index finger for the "p" key. On-screen instructions to remind participants of the response keys and the specific task instructions appeared on the screen on three separate lines. Instructions for inclusion were "Respond now", "1 = sequence 1 sounds MORE familiar", "2 = sequence 2 sounds MORE familiar" and instructions for exclusion were the same but the phrase "LESS familiar" was used instead. We collected confidence ratings on a scale between 50 and 100 after each forced-choice trial. Knowledge attribution ratings were "guess", "intuition" and "memory", which the participant recorded by pressing number keys 1-3 on the computer keyboard. The duration of each individual test sequence, and therefore the duration of the test phase, depended on the duration of each shape in the different speed conditions.

Refer to Appendix C for standardised verbal instructions

5.1.2.1.8 Additional measures: musical sophistication, IQ and working memory

In the same way as for our auditory experiment, we measured participants' perceptual abilities and musical training using the GOLD-MSI questionnaire (Appendix F.3), their reading ability through the NART (Appendix F.4), and their auditory and visual digit span. Overall, the experiment took no longer than 60 minutes.

5.1.2.2 Results

Differences between L1 and L2

There was no significant difference in the proportion of correct responses between participants trained on L1 and L2 under inclusion (p = .472) or exclusion (p = .373), therefore, the data was pooled for the purpose of subsequent analyses.

Process Dissociation Procedure

2AFC data was analysed separately under inclusion and exclusion instructions for the purpose of the PDP. In the fast presentation speed group, the proportion of training sequences chosen was above chance (0.5) under inclusion conditions (M = 0.53, SD = 0.09), t(26) = 1.732, p = 0.048, one-tailed, 95% CIs [-0.024 0.087], Cohen's d = 0.333, but at chance under exclusion conditions (M = 0.49, SD = 0.11), t(26) = -0.280, p = .781, two-tailed, 95% CIs [-0.066 0.054], Cohen's d = -0.054. The small size of the learning effect under inclusion instructions suggested that participants had only acquired little knowledge of the triplets in this speed condition. A paired-samples t-test showed that there was no significant difference between inclusion and exclusion in the proportion of training sequences chosen, reinforcing the fact that participants did not acquire much knowledge when shapes were presented at this speed, t(26) = 1.147, p = .262, 95% CIs of the difference [-.029 .103], Cohen's d = 0.221.

In the baseline presentation speed group, the proportion of training sequences chosen was significantly above chance (0.5) under inclusion conditions (M = 0.55, SD = 0.43), t(26) = 2.247, p = .017, one-tailed, 95% CIs [-0.012 0.119], Cohen's d = 0.432, and significantly below chance under exclusion conditions (0.43, SD = 0.15), t(26) = -2.245, p = .034, two-tailed, 95% CIs [-0.141 0.009], Cohen's d = 0.432, indicating that participants had control over the expression of their knowledge, that is, they could conform to exclusion instructions. This was confirmed by a paired-samples t-test showing that the proportion of training sequences chosen was significantly higher under inclusion than under exclusion instructions, t(26) = 2.519, p = .018, 95% CIs of the difference [0.022 0.216], Cohen's d = 0.485. We also compared the proportion of structured sequences chosen under inclusion (M = 0.55, SD = 0.12) to the proportion of unstructured sequences chosen under exclusion (*M* = 0.57, *SD* = 0.15) in a paired-samples t-test. The result was non-significant, $t(26) = -0.515$, $p = .611$, two-tailed, 95% Cis of the difference [-0.064 0.038], Cohen's $d = -0.099$, showing that participants were able to conform to exclusion instructions, and therefore that their knowledge was explicit.

Participants in the slow presentation speed group also chose training sequences significantly above chance under inclusion (*M* = 0.56, *SD* = 0.14), $t(27) = 2.407$, $p = .012$, one-tailed, 95% CIs [-0.007 0.132], Cohen's $d = 0.455$, and significantly below chance under exclusion (M = 0.40, SD = 0.14), $t(27) = -3.787$, $p = .001$, two-tailed, 95% CIs [-1.171 -0.030], Cohen's $d = 0.716$, again, indicating that they had control over the expression of their knowledge. A significantly larger proportion of training sequences was chosen under inclusion instructions than under exclusion instructions, $t(27) = 3.460$, $p = .002$, two-tailed, 95% CIs of the difference [0.066 0.260], Cohen's $d = 0.654$. Furthermore, a comparison of the proportion of structured sequences chosen under inclusion (*M* = 0.56, *SD* = 0.12) and the proportion of unstructured sequences chosen under exclusion (*M* = 0.60, *SD* = 0.14) showed a non-significant difference, $t(27) = -1.636$, $p = .114$, two-tailed, 95% Cis of the difference [-0.086 0.010], Cohen's $d = -0.309$, also indicating explicit knowledge.

Refer to Table 5.5 for descriptive statistics and to Figure 5.8 for a summary of 2AFC task performance under inclusion and exclusion instructions for the three speed groups (PDP), representing the mean proportion of training sequences chosen as a dependent variable.

Speed condition		**Mean (SD)**
Fast	**Inclusion**	0.53 (0.09)
	Exclusion	0.49 (0.11)
Baseline	**Inclusion**	0.55 (0.12)
	Exclusion	0.43 (0.15)
Slow	**Inclusion**	0.56 (0.14)
	Exclusion	0.40 (0.14)

Table 5.5: Descriptive statistics for the proportion of training sequences chosen under inclusion and exclusion instructions (PDP) separately for the three different conditions of speed.

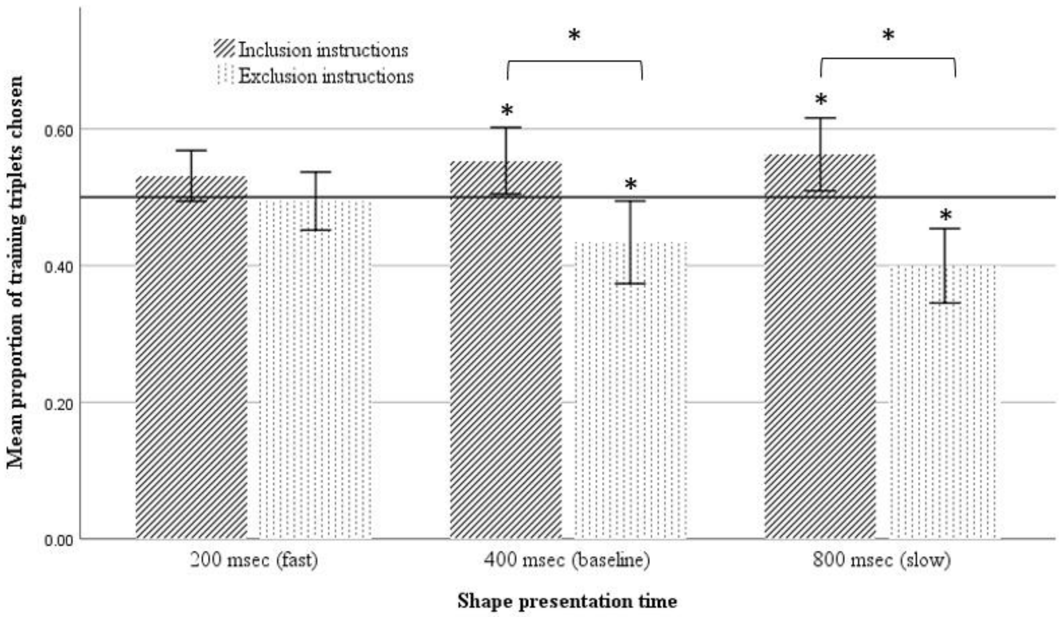

Figure 5.8: Mean proportion of training sequences chosen under inclusion and exclusion instructions (PDP) separately for the three different conditions of speed. Error bars represent 95% Confidence Intervals. Line represents chance level in the 2AFC (0.5). Conditions in which performance significantly differed from chance, as well as significant differences between pairs of conditions, are marked with one asterisk (*).

Guessing and zero correlation criteria

In order to evaluate whether there were differences in the proportion of guess, intuition and memory attributions chosen under inclusion and exclusion, two one-way repeated-measures ANOVAs were carried out with Attributions as the within-subjects factor. Under inclusion instructions, there was no significant difference in the choice of guess, intuition and memory attributions, for any of the speed conditions (all ps > .509) and the same results were obtained for exclusion instructions (all ps > .694), indicating that participants did not tend to privilege certain knowledge attributions over others. See Figures 5.9 and 5.10 for prevalence of different knowledge attributions in the three presentation speeds under inclusion and exclusion. These figures show the proportion out of the total 2AFC trials in which each of the different knowledge attributions was used.

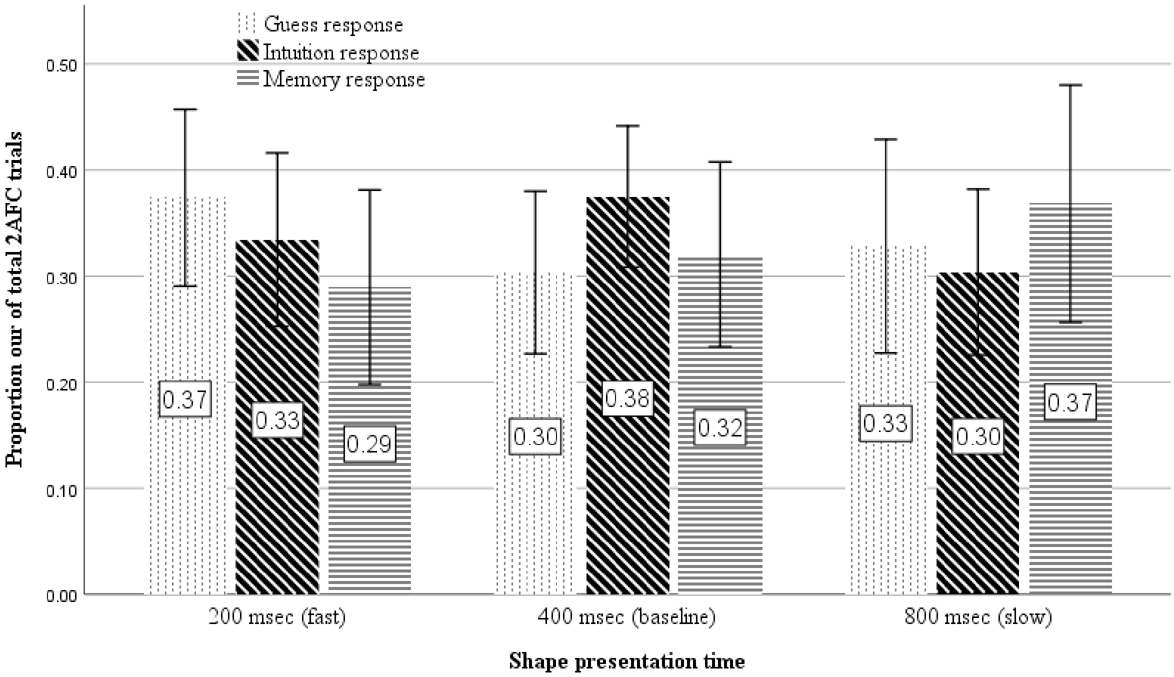

Figure 5.9: Proportion of 2AFC trials out of total in which guess, intuition and memory attributions were used, separately for each condition of speed under inclusion instructions. Error bars represent 95% confidence intervals.

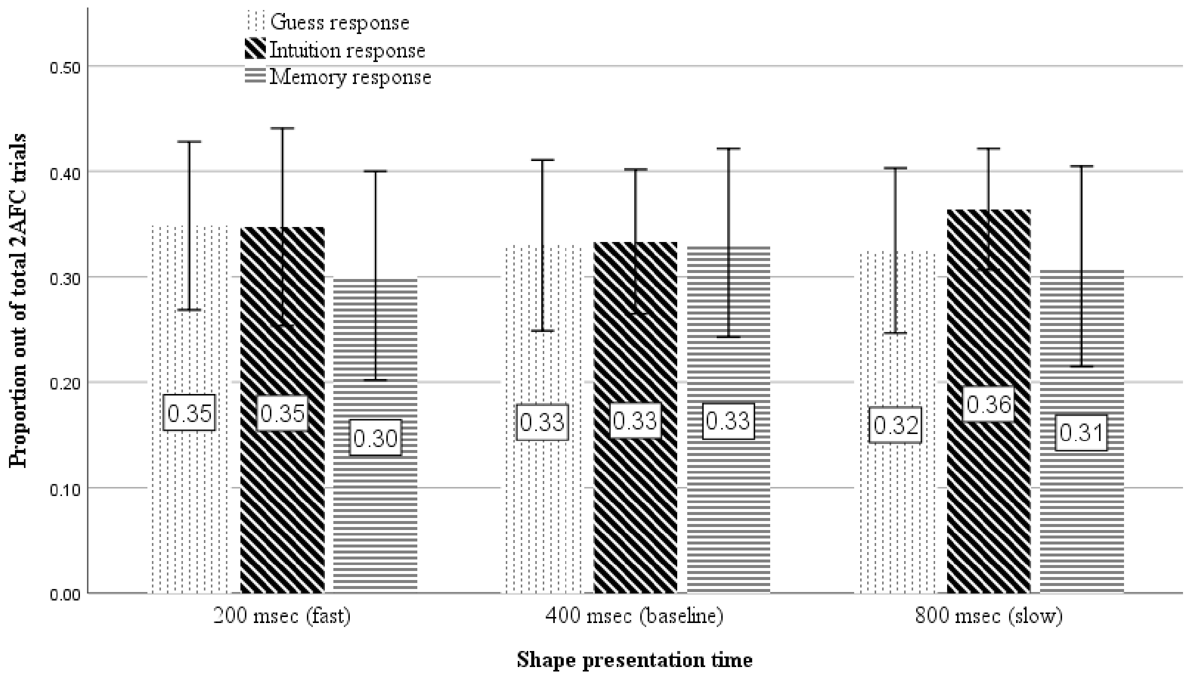

Figure 5.10: proportion of 2AFC trials out of total in which guess, intuition and memory attributions were used, separately for each condition of speed under exclusion instructions. Error bars represent 95% confidence intervals.

For the purpose of the guessing criterion, the proportion of correct responses in trials in which participants were guessing, using their intuition or their memory was compared separately to chance (0.5). This analysis was carried out for both inclusion and exclusion instructions. Participants performed above chance when guessing under inclusion in the fast stimulus presentation condition (p = .031, one tailed), which could be indicative of implicit knowledge. The fact that performance was at chance when participants were using their intuition and remembering could either reflect the participants' inability to track their knowledge, or, instead, could be due to the lower power of these analyses. In fact, the majority of knowledge attributions in this condition were guesses, and comparably fewer trials used intuition and memory attributions. The baseline condition seems to suggest that both implicit and explicit knowledge were present, as performance was above chance when guessing under inclusion ($p = .001$, one-tailed) but also above chance when participants were using their memory ($p = .005$, one-tailed). When data were analysed separately for trials in which guessing, intuition and memory were used in the slow condition, performance was at chance for all these knowledge attributions. This might be due to the low power of the analyses, but seems unlikely to be due to poor knowledge, as the slow condition was the one in which learning was observed with the largest effect size. With regards to the guessing criterion under exclusion conditions, performance was at chance for all knowledge attributions in all conditions of speed (all *p*s > .079). Results of the one-sample t-tests are displayed in Table 5.6.

			N	Mean (*SD*)	*t*	df	*p*	Cohen's *d*
Fast (200 msec)	**Inclusion**	**Guess**	27	0.56 (0.15)	1.948	26	.031*	0.375
		Intuition	23	0.53 (0.17)	.909	22	.187	0.190
		Memory	24	0.49 (0.23)	-.163	23	.436	-0.033
	Exclusion	**Guess**	27	0.50 (0.18)	.119	26	.906	0.023
		Intuition	26	0.49 (0.24)	-.119	25	.906	-0.023
		Memory	25	0.52 (0.28)	.395	24	.696	0.079
Baseline (400 msec)	**Inclusion**	**Guess**	27	0.62 (0.19)	3.389	26	.001**	0.652
		Intuition	26	0.52 (0.20)	.487	25	.315	0.096
		Memory	24	0.65 (0.26)	2.803	23	.005*	0.572
	Exclusion	**Guess**	27	0.52 (0.17)	.556	26	.583	0.107
		Intuition	26	0.55 (0.22)	1.197	25	.242	0.235
		Memory	25	0.61 (0.32)	1.762	24	.091	0.352
Slow (800 msec)	**Inclusion**	**Guess**	28	0.44 (0.22)	-1.503	27	.073	-0.284
		Intuition	25	0.54 (0.22)	.952	24	.176	0.190
		Memory	27	0.55 (0.32)	.807	26	.214	0.155
	Exclusion	**Guess**	27	0.54 (0.25)	.880	26	.387	0.169
		Intuition	24	0.54 (0.17)	1.058	23	.301	0.216
		Memory	26	0.62 (0.33)	1.831	25	.079	0.359

Table 5.6: One-sample t-tests comparing the proportion of correct responses for each of the three knowledge attributions to chance level (0.5) – guessing criterion. Results are displayed separately for inclusion and exclusion conditions and for condition of speed. Significant p-values are marked with one asterisk (*) for significance at the 0.05 level and two asterisks (**) for significance at the 0.01 level. Results for inclusion are one-tailed.

A summary of the guessing criterion for inclusion and exclusion instructions can be found in Figures 5.11 and 5.12, respectively. For the purpose of representing the guessing criterion, these figures depict the mean proportion of correct responses as a dependent variable.

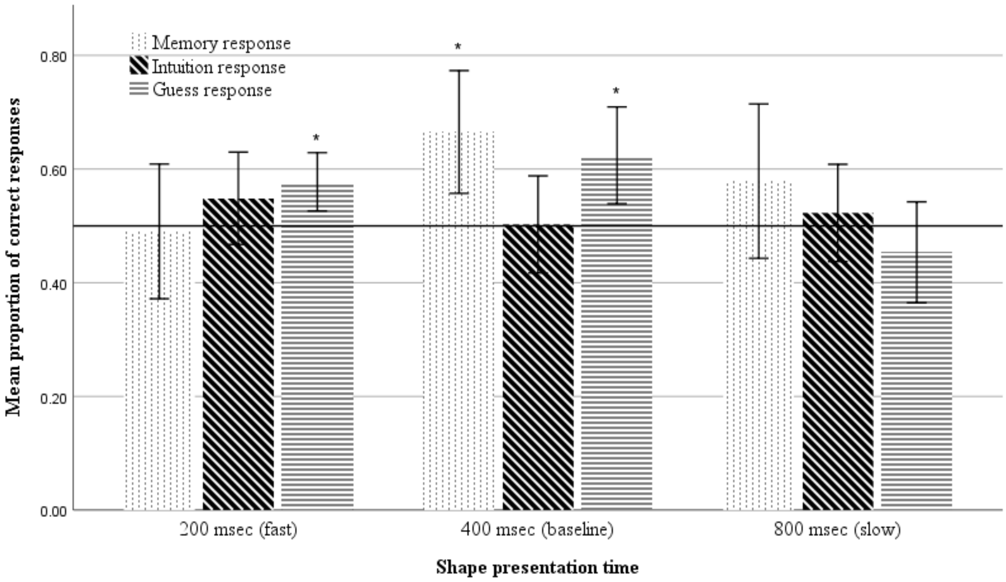

Figure 5.11: Mean proportion of correct responses in the 2AFC task separately for each type of knowledge attribution (guessing criterion) under inclusion instructions. Line represents chance level (0.5). Conditions in which performance was significantly different from chance are marked with one asterisk (*). Error bars represent 95% confidence intervals.

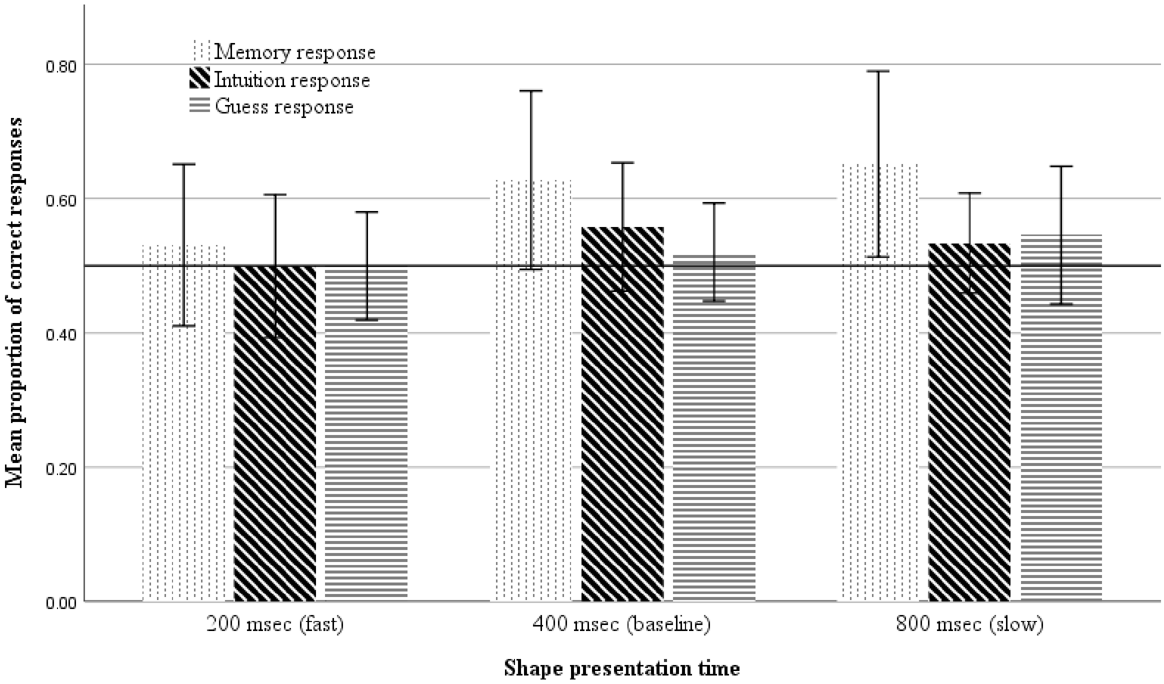

Figure 5.12: Mean proportion of correct responses in the 2AFC task separately for each type of knowledge attribution under exclusion instructions. Line represents chance level (0.5). Conditions in which performance significantly differed from chance are marked with one asterisk (*). Error bars represent 95% confidence intervals. Note that the proportion of correct responses under exclusion is the proportion of "new" or untrained sequences chosen.

For the purpose of the zero correlation criterion, a paired-samples t-test was carried out between confidence in trials where participants were correct and in trials when they were wrong. As can be seen in Table 5.7, the results were significant, with higher confidence when correct than when wrong only under exclusion and only in the baseline and slow speed conditions. Furthermore, it is also worth noting that these difference were much lower compared to the auditory experiment, suggesting that participants felt that the visual task was more difficult.

Speed	PDP condition	Response correctness	*N*	Mean (*SD*)	*t*	df	*p*	Cohen's *d*	95% CIs of the difference
Fast (100 msec)	**Inclusion**	**Correct**	27	64.99 (6.94)	0.460	26	.649	0.089	[-0.990 1.561]
		Incorrect	27	64.70 (7.00)					
	Exclusion	**Correct**	27	64.70 (6.89)	0.005	26	.996	0.001	[-1.578 1.586]
		Incorrect	27	64.69 (8.34)					
Baseline (200 msec)	**Inclusion**	**Correct**	27	68.97 (8.05)	1.042	26	.315	0.201	[-1.019 3.041]
		Incorrect	27	67.96 (8.64)					
	Exclusion	**Correct**	27	68.47 (9.35)	2.184	26	.038	0.420	[0.165 5.453]
		Incorrect	27	65.66 (9.01)					
Slow (400 msec)	**Inclusion**	**Correct**	28	68.74 (11.03)	1.039	27	.308	0.196	[-1.816 5.540]
		Incorrect	28	66.88 (9.37)					
	Exclusion	**Correct**	28	68.81 (10.71)	2.614	27	.014	0.494	[0.578 4.798]
		Incorrect	28	66.12 (9.08)					

Table 5.7: Results of paired-samples t-tests comparing confidence in trials when participants were correct and when they were incorrect (guessing criterion). Results are displayed separately for inclusion and exclusion conditions and for speed condition. Significant p-values are marked with one asterisk (*) for significance at the 0.05 level and two asterisks (**) for significance at the 0.01 level.

Triplet preference analysis

In order to assess whether there were any biases towards specific shape triplets, a one-way repeated-measures ANOVA was carried out on the number of times each of the four triplets from L1 and from L2 was chosen, regardless of correctness. Only the inclusion condition was considered in this analysis. For L1 triplets, no main effect of triplet type was found, $F(3, 243) = 1.820$, $p = .144$, $\eta_p^2 = 0.022$, indicating that there were no biases towards specific triplets. For L2 triplets, there was a significant main effect of triplet type, $F(3, 242) = 3.844$, $p = .010$, $\eta_p^2 = 0.045$. Pairwise comparisons showed that this effect was driven by a significant difference between triplets 2 and 4, as well as between triplets 3 and 4 (Figure 5.13).

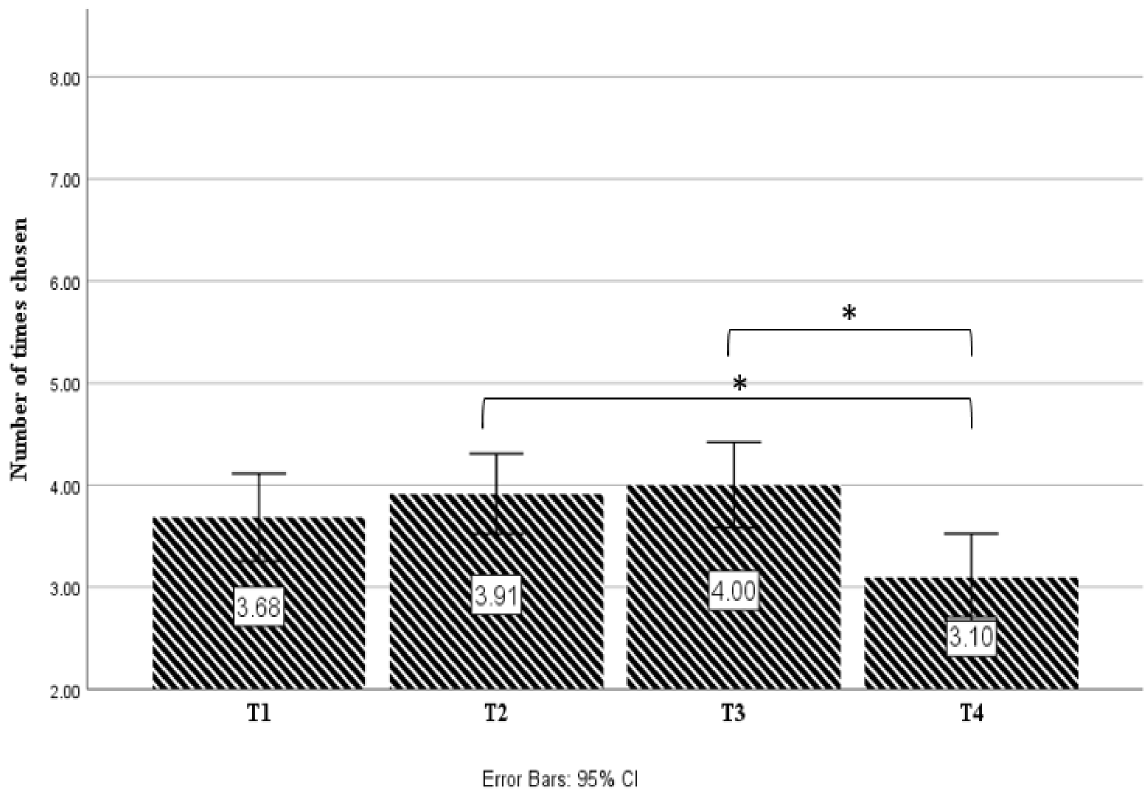

Figure 5.13: Average number of times each of the four L2 triplets was chosen under inclusion. Note the maximum number of times each individual triplet could be chosen was eight, as each triplet was

repeated eight times within the test phase. Significant differences between triplets according to pairwise comparisons is marked with an asterisk (*).

Correlational analyses

Correlations were carried out on the data pooled across conditions of speed, as we were interested in the correlation between visual statistical learning and other cognitive abilities regardless of speed. As shown in Table 5.8, the only relevant significant correlations observed were between NART scores and musical training and between auditory and visual digit span scores. Although these are interesting, they do not relate to visual statistical learning.

		1	2	3	4	5	6	7
1 NART score	***r***							
	p							
	N							
2 Auditory digit span	***r***	.138						
	p	.243						
	N	73						
3 Visual digit span	***r***	.097	.424**					
	p	.417	.000					
	N	72	72					
4 Perceptual abilities	***r***	.139	.099	.006				
	p	.217	.403	.958				
	N	80	74	72				
5 Musical training	***r***	.234*	-.035	.010	.482**			
	p	.038	.770	.932	.000			
	N	79	73	71	81			
6 Inclusion performance	***r***	.064	.088	.110	.036	-.060		
	p	.574	.454	.358	.749	.597		
	N	80	74	72	82	81		
7 Exclusion performance	***r***	.156	.144	.094	-.077	-.096	.559**	
	p	.166	.221	.431	.494	.392	.000	
	N	80	74	72	82	81	82	

Table 5.8: Correlation matrix illustrating the relationship between the proportion of correct responses under inclusion and exclusion conditions and our other variables of interest. Correlations significant at the 0.05 level (two-tailed) are marked with one asterisk (*) and correlations significant at the 0.01 level (two-tailed) are marked with two asterisks (**).

Individual differences analysis

It was apparent from the raw data that the majority of participants performed around chance level in our visual triplet learning task (Figure 5.14).

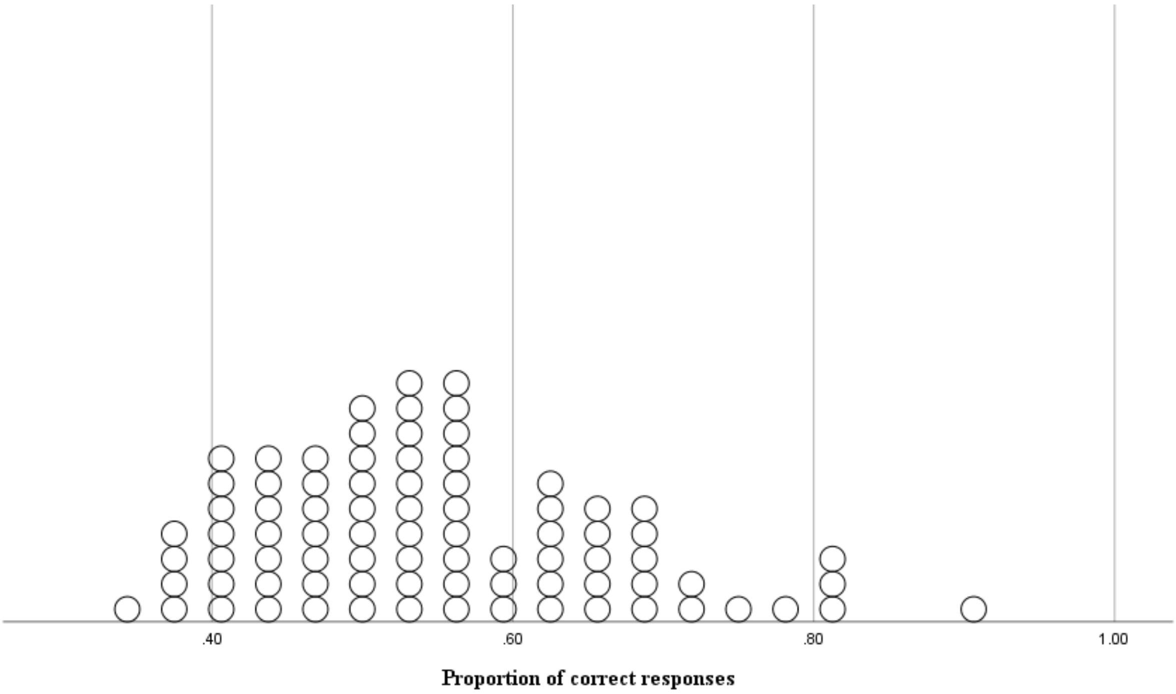

Figure 5.14: Simple dot plot of participants' performance in the 2AFC task, representing each individual's proportion of correct responses.

We were interested in investigating implicit and explicit knowledge only in those participants who performed above individual chance level, in order to assess the performance of our measures of conscious knowledge in participants who had acquired good knowledge of the statistical structure of the stimuli. The proportion of correct responses required to perform above chance individually was calculated to be 0.65[4], therefore participants who scored 65% correct or more in the 2AFC task

[4] The threshold for individual above-chance performance was calculated using the binomial distribution to obtain information on the probability of obtaining any one outcome and, through use of the cumulative distribution function, the probability of obtaining any outcome below or above a certain number of trials. Therefore, in order to compute, in MATLAB, the minimum number of correct trials required to be above

under inclusion were chosen as "good performers" for subsequent analyses. Given that, on average, participants acquired knowledge in all speed conditions, for the purpose of analysing knowledge in good performers, we pooled data for the three speeds of visual presentation. Eighteen out of our total of 82 participants were classed as "good performers" and included in subsequent analyses.

Process Dissociation Procedure

The proportion of training sequences chosen was significantly above chance (0.5) under inclusion instructions, (M = 0.72, SD = 0.07) $t(17) = 13.034$, $p < .001$, one-tailed, 95% CIs [0.169 0.279], Cohen's d = 3.072 and significantly below chance under exclusion instructions (0.34), $t(17) = 4.876$, $p < .001$, two-tailed, 90% CIs [-2.168 -0.077], Cohen's d = 1.149. Furthermore, the proportion of training sequences chosen was significantly larger under inclusion instructions (M = 0.72 SD = 0.07) than under exclusion instructions (M = 0.34 SD = 0.14), $t(17) = 8.216$, $p < .001$, two-tailed, 95% CIs of the difference [0.284 0.480], Cohen's d = 1.937 (Figure 5.15). This indicated that these participants held knowledge explicitly.

chance for a one-tailed outcome, we used the following formula: *N = 32; c = 2; L2 = binoinv(0.95,N,1/c)*, where N is the number of trials, 32 in the case of our 2AFC task, c is the number of choices per trials, based on only one correct choice in our 2AFC task, L2 is a vector containing the limit for above chance performance. A 5% alpha rate was used.

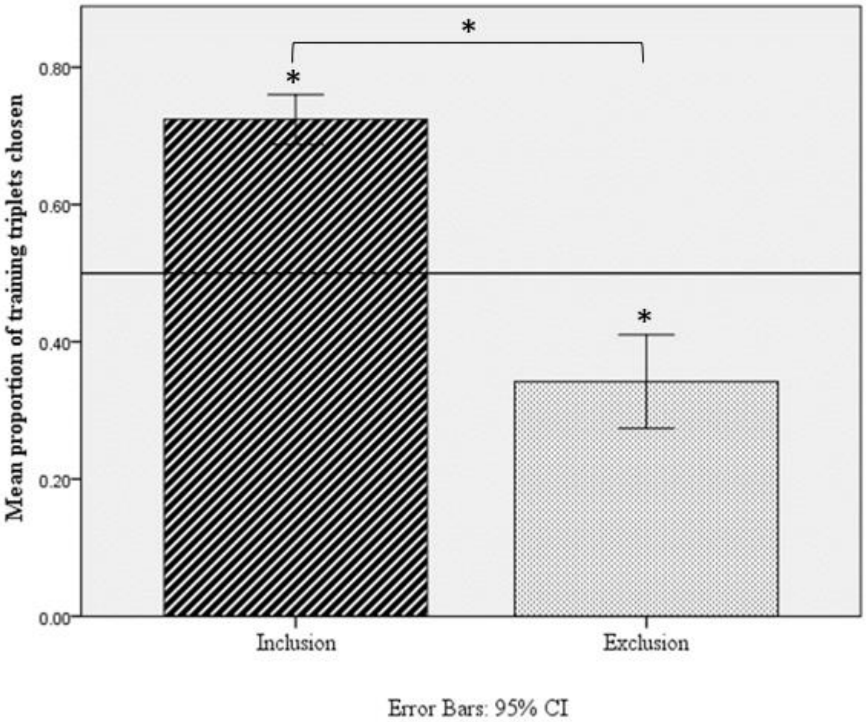

Figure 5.15: Mean proportion of training sequences chosen under inclusion and exclusion instructions (PDP) in good performers. Line represents chance level in the 2AFC (0.5). Conditions in which performance significantly differed from chance, as well as significant differences between pairs of conditions, are marked with one asterisk (*).

Guessing and zero correlation criteria

Under inclusion, participants performed at chance when guessing (p = 0.064, one-tailed) and significantly above chance when using their intuition (p < .001, one-tailed) and their memory (p < .001, one-tailed). Similarly, under exclusion, participants performed at chance when guessing (p = .073, two-tailed) and when using their intuition (p = .331, two-tailed), but above chance when using their memory (p < .001, two-tailed). See Table 5.9 for one-sample t-tests results. These results, according to the guessing criterion, indicate that knowledge was explicit.

		N	Mean (*SD*)	*t*	df	*p*	Cohen's *d*
Inclusion	**Guess**	18	0.59 (0.23)	1.596	17	.065	0.376
	Intuition	18	0.69 (0.15)	5.584	17	>.001**	1.316
	Memory	17	0.79 (0.16)	7.485	16	>.001**	1.815
Exclusion	**Guess**	18	0.60 (0.22)	1.908	17	.073	0.450
	Intuition	18	0.55 (0.21)	1.001	17	.331	0.236
	Memory	16	0.85 (0.16)	8.548	15	>.000**	2.137

Table 5.9: One-sample t-tests comparing the proportion of correct responses for each of the three knowledge attributions to chance level (0.5) – guessing criterion in good performers. Results are displayed separately for inclusion and exclusion conditions. Significant p-values are marked with one asterisk (*) for significance at the 0.05 level and two asterisks (**) for significance at the 0.01 level. Results for inclusion are one-tailed.

Results of the zero correlation criterion pointed in the same direction. Under inclusion, confidence in correct trials (M = 72.44, SD = 11.12) was significantly higher than confidence in incorrect trials (M = 66.63, SD = 9.32), t (17) = 3.283, p = .004, 95% CIs of the difference [2.075 9.537], Cohen's d = 0.774. The same results were obtained for exclusion: confidence when correct (M = 71.08 SD = 11.26) was significantly higher than confidence when wrong (M = 66.47 SD = 9.32), t (17) = 3.32, p = .004, 95% CIs of the difference [1.681 7.542], Cohen's d = 0.783.

Triplet preference analysis

In the same way as for our analysis on the whole sample of participants, in order to assess whether this participant group had any biases towards specific shape triplets, a one-way repeated-measures ANOVA was carried out on the number of times each of the four triplets from L1 and from L2 was chosen, regardless of correctness. Interestingly, no effect of triplet type was observer for L1 or L2 triplets.

Correlational analyses

Similar to the analysis carried out for the whole participant sample, no significant correlations relating to visual statistical learning and our additional measures were observed (Table 5.10).

		1	2	3	4	5	6	7
1 NART score	***r***							
	p							
	N							
2 Auditory digit span	***r***	.166						
	p	.539						
	N	16						
3 Visual digit span	***r***	-.329	.469					
	p	.213	.067					
	N	16	16					
4 Perceptual abilities	***r***	-.324	-.434	-.251				
	p	.190	.093	.348				
	N	18	16	16				
5 Musical training	***r***	-.041	-.531*	-.500	.254			
	p	.876	.042	.058	.325			
	N	17	15	15	17			
6 Inclusion performance	***r***	-.055	.006	.191	-.375	.063		
	p	.830	.984	.479	.125	.809		
	N	18	16	16	18	17		
7 Exclusion performance	***r***	.030	.043	.204	-.389	.025	.733**	
	p	.904	.875	.450	.110	.924	.001	
	N	18	16	16	18	17	18	

Table 5.10: Correlation matrix illustrating the relationship between the proportion of correct responses under inclusion and exclusion conditions and our other variables of interest. Correlations significant at the 0.05 level (two-tailed) are marked with one asterisk (*) and correlations significant at the 0.01 level (two-tailed) are marked with two asterisks (**).

5.1.2.3 Discussion

This experiment tested implicit and explicit knowledge in visual statistical learning. We were interested in whether the presentation speed of the visual shapes in a triplet learning paradigm affects the status of the knowledge acquired (implicit or explicit). For the purpose of assessing conscious knowledge, we used the PDP in combination with the guessing and zero correlation criteria.

In the fast stimulus presentation condition, results of the PDP suggested that participants did not acquire much knowledge of the triplets. In fact, performance was close to chance under inclusion conditions, with a small learning effect, and at chance under exclusion conditions. There was no difference in the number of training sequences chosen between inclusion and exclusion instructions, which indicated that participants had no control over their knowledge. This seems in line with results of the guessing criterion applied to the inclusion condition at this speed, which could indicate that some implicit knowledge was present, shown by above-chance performance in trials when participants were guessing, and by the fact that there was no difference in confidence between trials answered correctly and incorrectly. When applying the guessing criterion to the exclusion condition at this speed, the proportion of correct responses was not different from chance for any of the three knowledge attributions. This is not a surprising finding, and it is in line with the fact that not much knowledge was acquired in this condition, and that this knowledge was even more difficult to express under the more demanding exclusion instructions. Although these findings were at odds with those of previous similar studies, using a shape presentation time of 250 msec, (Bertels et al., 2015b) in which learning took place, and was primarily explicit, it is important to note that these authors used four times the amount of training as the present study with their participants, which appears to suggest that there is an interaction between speed of visual presentation and amount of training, whereby a high amount of training is needed at a fast stimulus presentation for explicit learning to occur, whereas at a slow speed of stimulus presentation, both a small amount and a large amount of training can produce explicit knowledge.

Knowledge in the baseline speed group was explicit according to the PDP. However, the guessing criterion applied to the inclusion condition suggested that some implicit knowledge was present as well, as indicated by above-chance performance in trials in which participants were guessing, although participants also performed above chance in trials in which they were using their memory. Implicit knowledge was confirmed by the zero correlation criterion, with no difference in confidence between trials in which participants were correct and trials in which they were incorrect. When applying the guessing criterion to exclusion performance, similar to the fast speed group, the proportion of correct responses was at chance for all knowledge attribution types. We suggest that this finding may be due to the fact that the learning effect in this visual triplet learning experiment was not large and, therefore, even though the PDP indicated that participants were able to control their knowledge by conforming to the exclusion instructions, when analysing the three types of knowledge attributions separately, therefore isolating trials for guessing, intuition and memory, due to the reduced power of these analyses, performance resulted at chance level.

In the slow shape presentation speed group, the PDP suggested that explicit knowledge was present. However, when applying the guessing criterion, knowledge was found to be at chance for each of the three knowledge attribution types, both for inclusion and exclusion. This is a surprising finding, as we would have expected knowledge to be at chance when guessing and above chance when using memory and, possibly, intuition, for these results to be in line with those of the PDP. We suggest a similar account for these findings to that outlined above, that is, the potentially low power of the statistical analyses used to analyse the three types of knowledge attributions separately, which resulted in the guessing criterion not yielding any useful information about implicit and explicit knowledge.

Another surprising finding in this experiment concerned the zero correlation criterion, and the fact that the difference in confidence between correct and incorrect trials was only significant for exclusion instructions in the baseline and slow presentation speed groups. No significant results were found under inclusion instructions. One potential explanation for this finding, which would be in line with the PDP results, could be that because, within the PDP, successful exclusion performance relies entirely on explicit knowledge, this is the condition in which differences in confidence between correct and incorrect trials are more likely to emerge. This account also reinforces our interpretation of both implicit and explicit knowledge in the baseline presentation speed, and suggests that there might be some implicit knowledge in the slow presentation speed condition as well, otherwise we would have observed a difference between confidence when correct and confidence when wrong in the inclusion condition.

Despite the account just outlined fits well in the context of our other results, the alternative possibility that these findings might reflect a methodological flaw of the zero correlation criterion needs to be considered. In fact, the lack of a difference between confidence in correct and incorrect trials, except for under exclusion instructions in the baseline and slow presentation speed groups, could reflect the fact that participants, generally, had low confidence in their responses, and therefore not be a genuine representation of whether they were aware of their knowledge. This proposal finds support in the fact that the learning effects observed in this visual triplet learning task were not large, and substantially smaller than the learning effects observed in our auditory speed experiment within this study.

This experiment also found that participants, within the L2 triplets, preferred certain triplets over others. Specifically, they preferred Triplet 2 and triplet 3 over Triplet 4. Triplet preference effects were also observed in Chapter 4 of this thesis, where we found that Triplet 3 of L1 was correctly completed most of the times. If the preference for certain shapes is what drives this triplet preference effect, it is surprising that we did not observe a triplet preference effect for Triplet 2 of L1 in the present experiment. Future studies using the visual triplet learning paradigm should be wary of this bias towards certain shapes, which could potentially cloud any learning effects in the task.

With regards to the results of our correlational analyses, no significant correlations were observed in this experiment other than the correlation between scores in the NART test and musical training. This replicated the results obtained in our auditory experiment within this study, and reinforced our confidence in this effect. As we argued earlier on, we believe that this significant correlation could be explained by the participants' socio-economic background, in that it is possible that participants who have been exposed to wider reading during childhood and adolescence, which may make them better performers in the NART test, have also received musical training as part of their upbringing. In future studies, for a more genuine assessment of IQ, we will select a measure which is less dependent on demographic variables such as a participants' socio-economic background. The lack of a significant correlation between 2AFC task performance and the perceptual abilities scores of the GoldMSI was in contrast with the findings of our auditory study, and suggests that this measure of musical sophistication may be primarily focused on auditory abilities and therefore less relevant for auditory statistical learning.

The large majority of our participants performed around chance level in the 2AFC task, and we hypothesised that this could play a role in the surprising effects that we observed with regards to the guessing and zero correlation criteria. To address this hypothesis, we carried out an additional analysis, which focused on good performers only. The PDP indicated that knowledge in these learners was explicit. This was in line with results of the guessing criterion, which suggested that participants held knowledge explicitly both under inclusion and under exclusion conditions: performance was at chance when guessing, above chance when using memory, and, when using intuition, above chance under inclusion and at chance under exclusion. Results of the guessing criterion also indicated that participants had explicit knowledge both for inclusion and exclusion.

Based on this analysis, we concluded that in the good learners, knowledge is fully explicit, in the sense that these participants have control of their knowledge and display awareness of what they know according to both the guessing criterion and the zero correlation criterion. These data did not provide any evidence of implicit knowledge in this group, which raises an interesting question around causality, specifically, whether these participants are good performers because of their use of explicit knowledge, or whether they have developed explicit knowledge as a result of being good performers. As our adopted definition of implicit in this thesis is “unaware”, this would fit in well with the hypothesis that stronger performance would also lead to greater awareness in participants, even if that awareness was not what originally led to their strong performance. As the question of performance in statistical learning tasks might be linked with the question of the development of explicit knowledge in participants, future research, in line with recent suggestions (Siegelman et al., 2017) might benefit from a greater focus on understanding the sources of individual differences in this type of learning.

Interestingly, the good performers did not show a preference for certain triplets over others, which leads to the suggestion that, when participants have acquired knowledge of the training triplets, they are less likely to be influenced by biases towards individual shapes or arrangements of shapes in the forced-choice test. With regards to the zero correlation criterion, it is interesting to see that, whilst there was no difference in confidence between correct and incorrect trials when data for all participants was pooled, a significant difference emerged in our analysis of good learners. This reinforces our proposal put forward earlier on that, when the learning effect is small, and participants’ confidence is low, the guessing criterion is not able to provide useful information on awareness of knowing.

Measures of musical sophistication, auditory and visual digit span and NART scores did not correlate with visual statistical learning in the high performers group. This result has increased our confidence that this lack of significant correlations is a genuine effect, and not due to the fact that statistical learning was poor for the majority of our participants.

Finally, a methodological point needs to be raised with regards to our implementation of the PDP in the context of our forced-choice task. In Chapter 1 and Chapter 3 we collected participant responses through keys 1, to choose sequence 1, and 2, to choose sequence 2 on the keyboard. Potentially due to the fact that these keys were placed next to each other, a number of participants had inverted their responses by pressing the opposite key to the one intended (instances of inversion are recorded in Appendix F.5). In order to tackle this issue, starting from, and including, Chapter 4 of this thesis, we changed the response keys to be at opposite sides of the keyboard (keys “q”, labelled as “1” and “p”, labelled as “2”), and instructed participants to respond using separate hands instead. This methodological change reduced the number of instances of inversion from 30% in Chapter 3 to 3.66% in the present chapter (Appendix F.5), with no instances detected in Chapter 4[5] although, interestingly, it did not completely eliminate the problem. Although it only occurred in a small proportion of participants, it is important to take this challenge into consideration in future implementations of the PDP in the context of forced-choice tasks. Despite the precautions taken in the experiment to ensure that participants correctly understood the task, it is possible that, for a small subset of our participants, the PDP instructions may have been too complex.

5.1.3 Conclusions

This study investigated changes in implicit and explicit knowledge in statistical learning at three different speeds of stimulus presentation (fast, baseline and slow) in the visual and auditory modality. Overall, our data suggested that learning can take place at all three presentation speeds, although participants’ knowledge is weaker at faster stimulus presentation speeds and stronger at slower stimulus presentation speeds. In the auditory modality both implicit and explicit knowledge were present in the fast presentation speed group, and we could not rule out the presence of some implicit knowledge in the slow presentation speed group. Knowledge was entirely explicit when tones were presented at the baseline speed. In the visual modality, knowledge was implicit when presentation speed was fast, both implicit and explicit in the baseline presentation speed group, and mostly explicit in the slow presentation speed group, although we could not entirely rule out the presence of implicit knowledge in this condition.

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[5] Note that in Chapter 3 instances of inversion only occurred in the visual experiment and therefore the 30% figure was calculated as a percentage of the total number of participants tested for the visual experiment only. Interestingly, in the present chapter, inversions also only occurred in the visual version of the experiment, therefore the 3.55% figure was calculated as a percentage of the total number of participants tested for that modality only.

Overall, in this study knowledge appeared more implicit at faster stimulus presentation speeds, and more explicit at slower speeds. This confirmed our original hypothesis that speed of stimulus presentation does, indeed, affect the status of conscious knowledge. We go further in suggesting that theories on the effects of speed developed within motor learning (Destrebecqz & Cleeremans, 2001; Cleeremans, 2003) may also be applicable to our two non-motor learning paradigms used in this study. As our pattern of findings applied to both the visual and auditory modality, we contradict previous evidence (Conway & Christiansen, 2009), that a faster stimulus presentation speed only negatively impacts task performance in the visual but not the auditory modality, although it is important to note that the fast auditory presentation speed used by these authors was slower than our fast presentation speed.

This study also raised some important methodological caveats relating to the application of the guessing and zero correlation criteria. The findings of this study suggest that, if participants find the task difficult, leading to low confidence, these two measures of conscious knowledge do not yield any useful information about awareness of knowledge.

With regards to individual differences, the present study suggests that, within musical sophistication, perceptual abilities are related to inclusion performance in auditory statistical learning. No correlation was observed between inclusion performance and musical training, which is a surprising finding, given evidence that musicians are better able to track the statistical properties of the input stimuli (Mandikal Vasuki et al., 2017). No significant correlations relevant to visual statistical learning were found either in the visual experiment. This could be because the visual triplet learning task might more heavily rely on strategies for successful performance, such as making familiarity judgements between patterns of shapes (Turk-Browne et al., 2005), which are not related to perceptual abilities in music. This leads us to the important suggestion that the auditory and visual tasks, despite both being statistical learning tasks, and thought to rely on the same basic mechanism of extraction of transitional probabilities between elements in the input stimuli, are, in fact, dependent on different processes for successful performance. Lastly, the results of both the visual and auditory experiment pointed to the need for a genuine measure of general IQ, which is not dependent on the participants' level of education and socio-economic background. With a view to better answering the question of the relationship between statistical learning and IQ, we suggest that future research should specifically focus on Fluid IQ and Performance IQ. An example of a well-known test that future research could focus on is Raven's Progressive Matrices, which requires participants to identify missing elements within a pattern

(Stankov, 2000). Subtests of the Wechsler Intelligence Scales, which focus on fluid reasoning, and also rely on matrix and series completion tasks (Canivez, Watkins & Dombrowski, 2016), would also be useful. We suggest that, due to their specific focus on inductive and deductive abstract reasoning, tests such as this may be more suitable candidates for the investigation of correlations with Statistical Learning abilities.

Chapter 6 The ERP correlates of implicit and explicit knowledge

6.1 Introduction

Our experiments so far in this thesis have found that Statistical Learning uses mainly explicit knowledge, with some indications of implicit knowledge. The guessing and zero correlation criteria, specifically, have, at times, reported findings which were in contradiction with results of the PDP, as well as with each other. At this stage in our research, it was necessary to address the possibility that behavioural measures of performance may not be sensitive enough to detect learning. Chapter 4 of this thesis aimed to address this possibility behaviourally, through the use of an RSVP task, which was primarily intended to ensure that no relevant knowledge was left undetected by the forced-choice tasks. However, despite our findings that the RSVP task did not detect any additional knowledge, we could not rule out the possibility that, in our behavioural experiment, memory processes might be taking place which do not influence behavioural performance. Given the well-known advantages of the ERP approach, such as the fact that it allows to measure learning online, as it happens, and its ability to detect effects for which behavioural measures lack sufficient sensitivity (Voss & Paller, 2008; Woodman, Geoffrey, 2010), we believed that, within the context of our research, this EEG study would be crucial in reflecting any cognitive processes than might have remained undetected up to this point.

Furthermore, throughout our research so far, it had emerged that the majority of participants perform around chance level in the visual triplet learning task with, typically, only a few good performers present within the sample. This is an aspect of visual triplet learning experiments which has recently been brought to attention in this field of research (Siegelman & Frost, 2015), and, despite our attempts to attribute these individual differences in behavioural performance to a variety of cognitive factors (through our correlational analyses in Chapter 5) we had not been able to clearly discover the source of this individual variability. Within this context, we believed that a combination of behavioural and electrophysiological measures, and a comparison of ERPs in learners and non-learners would be greatly beneficial to our understanding of implicit and explicit knowledge in statistical learning.

We believed that our research at this point would also greatly benefit from the study of implicit and explicit processes separately at learning (exposure) and retrieval. One of the main shortcomings of behavioural measures of performance is that, as they are retrospective in nature, they are merely based on an inference of implicit and explicit processes during the exposure phase, but might not necessarily represent processes that were taking place during exposure. This shortcoming is something that has been acknowledged early in ERP research on Statistical Learning (Eimer et al., 1996). In our case, we believed that ERPs would overcome this problem by allowing online measurement during the exposure phase. This would allow to obtain a measure of the brain response to to-be-learned items as learning happens. In this sense, we reasoned that the online measurement which electrophysiological investigations allow would be useful in overcoming the methodological shortcoming of behavioural measures of implicit and explicit knowledge.

There have been very few approaches to measuring learning online through behavioural methods in Statistical Learning. We maintained that, as this presents a large methodological challenge in the field, the few measures that have been developed do not constitute an accurate reflection of on-line learning. Karuza, Farmer, Fine, Smith, & Jaeger (2013) developed an entirely-behavioural on-line measure of learning which involves looking at the sequentially-presented visual stimuli on the screen in a self-paced manner, through the use of a moving-window display. In this paradigm, learning is measured as the difference in looking times between predictable and unpredictable items. Another attempt to capture learning on-line through behavioural-only measures is documented in a triplet learning study by (Franco, Gaillard, & Destrebecqz, 2014), and involves a click detection task which requires speeded responses by the participants. The authors criticise this method themselves, in that the response times obtained were not related to word segmentation in their data. Instead, they suggest that their click detection task might have interfered with successful learning.

There is also evidence that encoding and retrieval processes related to implicit and explicit memory might be different in nature and dissociable (Paller, Hutson, Miller, & Boehm, 2003; Schott et al., 2002), which provides one more reason to investigate them separately. ERPs would allow to study implicit and explicit knowledge separately in these two stages, something that is impossible to achieve through behavioural measures alone.

Neuropsychological research into explicit and implicit learning and knowledge has provided evidence that the two are, indeed distinct. Imaging data supports the idea that implicit and explicit sequence learning utilise different brain regions (Aizenstein et al., 2004; Yang & Li, 2012; Ferdinand, Rünger, Frensch, & Mecklinger, 2010). However, studies investigating the ERP correlates of implicit and explicit knowledge have faced a methodological issue around process purity. In fact, developing a knowledge test that is exclusively sensitive to implicit or explicit knowledge has been an ongoing challenge in this area, as performance in any behavioural test of implicit or explicit knowledge could be underpinned by either an implicit or explicit memory process, or a combination of both. This implies that any neural measures of knowledge might also be contaminated by a combination of knowledge types (Voss & Paller, 2008). Based on these premises, it is important for the purpose of ERP investigations that implicit and explicit processes are separated as best as possible.

One approach that has been adopted to address the issue of process purity is to distinguish explicit and implicit knowledge according to whether participants had an intention to learn the rules in the sequence. Rüsseler, Kuhlicke, & Münte, (2003b) adopted this approach in an SRT task. They divided their participants into a group of "intentional learners" and a group of "incidental learners", based on task instructions. While participants in the intentional learning groups were told to try to learn the sequence, participants in the incidental learning group were not informed of the presence of the sequence. The authors found an enhancement in N2b and P3b for deviants in the intentional but not the incidental group. These ERP responses were taken to reflect conscious processing. Importantly, although these ERP effects of deviance were only seen in the intentional learning group, response time data indicated that learning occurred for both groups. Another study by Rüsseler, Kuhlicke, et al., (2003b), operating the same distinction between "explicit learners" and "implicit learners" in a variation of the SRT task, found that, although both groups of participants showed evidence of learning (based on RT patterns), a greater error-related negativity (ERN) was elicited in explicit learners, possibly because the explicit search for a sequential regularity led to greater engagement of the error-monitoring system.

Another popular approach to separate implicit from explicit knowledge has been to distinguish the two on the basis of whether explicit knowledge of the regularities has been acquired or not, therefore, on the basis of participants' behavioural performance in a test. An early study by Eimer et al., (1996) adopted this approach by analysing both behavioural and electrophysiological measures of learning separately for participants who exhibited explicit knowledge of the sequence and those who did not. They found that deviant stimuli had a significant effect on N2 and P3 amplitude, with greater amplitude for deviant than standard stimuli. The N2 effect was larger, and present only for participants in the "explicit" group, suggesting that these amplitude effects are related to the amount of explicit knowledge held by participants.

A study by Fu et al., (2013) provides a sophisticated approach to solving the problem of process purity by using the Process Dissociation Procedure (PDP). Using a serial four-choice reaction- time task, the authors divided triplets into "explicit triplets" and "implicit triplets" on the basis of behavioural data obtained through the PDP. The authors argue that the PDP is a stricter measure of conscious knowledge, which ensures that there is no contamination of implicit knowledge by explicit knowledge and that procedural knowledge is not accompanied by explicit knowledge. They also warn against a fallacy of previous studies, such as Schlaghecken, Stürmer, & Eimer's (2000), in which explicitly-learned chunks of the training sequence included parts of the sequence that participants have explicitly learned, while implicitly learned parts may have included a mixture of implicitly-learned and unlearned parts of the sequence, therefore making it difficult to detect ERP components to implicitly learned parts of the sequence. The study by Fu et al., (2013) is evidence in favour of a specific association of N2 with implicit knowledge, and of P3 with explicit knowledge.

More recent ERP research has focused on the visual and auditory triplet learning paradigms and seems to have discovered clear indices of triplet segmentation. In an auditory triplet learning study, Abla, Katahira, & Okanoya (2008) found differences between learners and non-learners in the N400. The authors argue that the N400 effect indicates not only that segmentation has taken place but also to what extent. In a very similar study, Abla & Okanoya, (2009) used visual shapes and found that the N400 effect also applies to the visual modality. Mandikal Vasuki et al., (2017) refer to the larger N1 and N400 components for shapes in position 1 within a triplet than shapes in position 2 and 3 as the "triplet onset effect".

Very little research, however, has investigated the electrophysiological correlates of implicit and explicit knowledge in visual triplet learning, although there is fMRI evidence for dissociations between explicit familiarity and neural markers of learning, which appear to support learning outside of conscious awareness in this paradigm (Turk-Browne et al., 2009).

This study aimed to discover whether different ERP correlates could be observed for implicit and explicit knowledge in Statistical Learning, as well as to assess the sensitivity of the behavioural measures of conscious knowledge that we had used so far in our work. It was, in fact, intended to detect any knowledge that may have remained undetected by our behavioural tasks.

One important caveat regarding studies which aim to assess implicit and explicit knowledge in Sequential Regularities Learning is that, as a necessary part of the design, the distinction between implicit and explicit parts of the to-be-learned sequences is made on the basis of the behavioural measures available in the task, and is therefore subject to the same methodological shortfalls that may characterise these. Within this context, electrophysiological approaches to this question should aim to identify ERP components that are only present in participants who show explicit knowledge but not in participants who do not show this type of knowledge. This was the goal of the present study, which aimed to discriminate between implicitly and explicitly-learned information in order to identify specific components associated to each type of knowledge. We believed that this information would be crucial for future experiments and we suggest that future investigations in this area should also focus on a combination of behavioural and electrophysiological measures.

Based on previous ERP research with the SRT task, which has used sophisticated behavioural methods to distinguish between implicit and explicit fragments of the learning stimuli (Fu et al., 2013), in the present study we expected to observe an N2 response for implicit knowledge and a P3 response for explicit knowledge. We also expected a "triplet onset effect" (Vasuki et al., 2017), that is, larger N1 and N400 components for shapes in position 1 than position 2 and 3 within a triplet. In order to verify learning of the training triplets beyond the behavioural results, we measured ERPs to training (old) and unseen (new) triplets. Based on the well-known FN400 effect, also called the mid-frontal old/ new effect (Ferdinand et al., 2010; Voss & Paller, 2008), we expected to see more positive ERPs for old than new items. In our RSVP task, we hypothesised that we would see a larger P300 component for targets than non-targets, reflecting motor decision mechanisms (Rose et al., 2011).

6.2 Materials and methods

6.2.1 Participants

Twenty-five participants took part in the experiment. All participants were undergraduate students at the University of Lincoln, who participated in exchange for research credit points, or postgraduate students, who participated voluntarily. There were 4 males (age range = 19-28 years, mean age = 21.75, *SD* = 4.19) and 21 females (age range = 18-36 years, mean age =20.33, *SD* = 3.73). All participants had normal or corrected-to-normal vision. Participants were made fully aware of the exclusion criteria for the EEG, therefore no participant had any medical condition which could have put their safety at risk during the experiment. No participant had any other condition which could have affected the validity of the data.

6.2.2 Ethics

The study received ethical approval from the University of Lincoln Psychology Research Ethics Committee (see Appendix A for ethical approval form and full details of ethical approval). Participants were fully informed regarding the EEG methodology, and the exclusion criteria for the experiment. They provided full informed consent and were free to withdraw from the study at any point without providing any motivation, or to withdraw their data at a later point. At the end of the experiment participants were fully debriefed, verbally and in writing (See Appendix G for participant information sheet, consent form and written debrief form).

6.2.3 Stimuli

The stimuli for this experiment were identical to those used in Chapter 5, and consisted of the same L1 and L2 triplets as those used in that experiment. Given that we did not observe any significant differences in performance between L1 and L2 in Chapter 5, we trained all our participants on L1, and used triplets from L2 as the untrained language. Shapes were displayed on the screen for 500 msec with an ISI of 250 msec, giving 750-msec-long epochs, which were considered a sufficient duration for successful recording of ERPs, based on previous research of a similar nature (Abla & Okanoya, 2009).

6.2.4 Apparatus

The experiment program ran on MATLAB R2017a on a Dell computer running a Windows 7 Home Premium operating system with an Intel ® Core ™ i7-3770 Processor. Visual stimuli were presented in colour on a 22-inch Iiyama Vision Master Pro 514 CRT monitor. EEG data was collected through a Dell Precision computer with an Intel ® Core Duo running an XP operating system, and a BioSemi system (Active Two 256 channel AD-box) was used to record and amplify EEG data (www.biosemi.com). Participant responses were collected through a DELL keyboard. In order to minimise head movements, and to keep eye-to-screen distance constant, we asked participants to rest their chin on a chin rest.

6.2.5 Procedure

The procedure for this experiment was very similar to that of our visual triplet learning experiment in Chapter 5, with the addition of the RSVP task, carried out in a similar way to Chapter 4. Tests were administered in the following order: exposure phase, RSVP task, 2AFC task (inclusion and exclusion). ERPs were recorded for the whole duration of the session.

6.2.5.1 ERP recording and data pre-processing

The experiment took place in a Faraday-shielded room, where participants sat at a viewing distance of 65 centimetres from the computer screen. In order to obtain both behavioural and electrophysiological measures for each of our tasks, ERPs were recoded from the beginning to the end of the experiment.

The EEG recording was set up using the standard 10/20 system (Milnik, 2009), which involved collecting data from sixty-four Ag-AgCL electrodes with the aid of an EEG cap to identify electrode locations. In addition to this, EOG was recorded for the purpose of measuring vertical and horizontal eye movements. The EEG signal was sampled at 256 Hz and band-pass filtered between 1 and 40 Hz.

We used the Matlab Toolbox EEGLAB (Delorme & Makeig, 2004) for data pre-processing and the Toolbox ERPLAB (Lopez-calderon & Luck, 2014) for data analysis. As part of pre-processing, data were re-referenced to the left and right mastoid channels. Data were epoched from -200 msec to 750 msec with a -200 to 0 msec (visual stimulus onset) baseline. We removed artefacts from data using first using the Gratton-Coles algorithm (Gratton, Coles & Donchin, 1983) to specifically remove vertical eye movements (blinks), using a 20-msec time window and a threshold for blink removal of 10 msec. Afterwards, we inspected data through a moving time window of 200 msec shifting in steps of 50 msec. Epochs were rejected if the peak-to-peak voltage exceeded 200 Volts, a threshold which we set for the purpose of removing larger artefacts, such as muscle movements. Data were also visually inspected for electrodes with poor signal and these electrodes were removed from analysis. No participants were removed from analysis as a result of poor data quality.

6.2.5.2 Exposure phase

The exposure phase was almost identical to that used in Chapter 4 of this thesis. It consisted of 96 triplets, each appearing 24 times during exposure, which added up to a total of 288 shapes.

The only difference between the exposure phase used in Chapter 4 and the present exposure phase was that, in order to have a larger amount of trials for the purpose of ERP analysis, the symbolic exposure stream was concatenated with itself to obtain twice the number of exposure trials, therefore adding up to 576 exposure trials. We used the same distractor task as the one used in Chapter 4, in which participants were asked to respond by pressing the space bar as quickly as possible to presentation of a distractor stimulus (a cartoon character). The sole aim of this task was to maintain participants' attention to the exposure stream. For consistency with our experiment in Chapter 4, a distractor appeared on roughly 5% of exposure trials. There were, in fact, 28 distractor stimuli in our exposure stream, which produced a total of 604 exposure trials. For the purpose of the EEG recording, 1-second long blink breaks were also introduced within the exposure stream. Blink breaks were placed roughly every 10 trials and consisted in a message coming up on the screen with the instructions "please blink now". In total, the exposure phase lasted just over 8 minutes.

6.2.5.3 Test phase

6.2.5.3.1 RSVP

The implementation of our RSVP task in this experiment was very similar to that of the RSVP task in Chapter 4, with two exceptions. Firstly, the presentation time for each shape was changed to 500 msec, with a 250 msec ISI, in keeping with 750-msec-long epoch durations. Secondly, each test trial was formed by concatenating the 12-element test stream with itself, in order to double the number of overall trials for the purpose of accurate ERP analysis. This meant that each test stream was 24-elements long and contained the target shape twice, due to the concatenation, and therefore required two responses to the target shape. All other experiment parameters were the same as for the RSVP task used in Chapter 4. The RSVP task took approximately 15 minutes to complete.

6.2.5.3.2 Two-alternative forced-choice task

The behavioural 2AFC task for this experiment was similar to that of our visual triplet learning experiment in Chapter 5, both in terms of test parameters, and use of the PDP to distinguish implicit from explicit knowledge. However, for the purpose of accurate EEG analysis, we doubled the number of test trials from 32, in our previous visual triplet learning experiments, to 64. Therefore, each of the four triplets appeared 16 times within the test phase. We also decided to use binary knowledge attribution ratings, labelled as “guess” and “memory”, and discarded the “intuition” knowledge attribution rating. This was to ensure that there would be a high enough number of guess and memory trials to meaningfully analyse for the participants’ ERP responses. Furthermore, some authors have suggested that the relationship between confidence and accuracy is stronger when binary confidence ratings are used (Tunney & Shanks, 2003).

6.3 Results

6.3.1 Behavioural results

Exposure phase – analysis of distractor task

In the same way as for our exposure results in Chapter 4, we established a time window for detection of the distractor from 150 msec to 750 msec post-distractor. This choice was consistent with our analysis of exposure in Chapter 4 of this thesis, in which the distractor detection time window went from 150 msec post distractor onset to onset of the next shape, but also reflected the longer shape presentation times of the current experiment. Any response times following outside this time window were considered as a missed response. A 60% distractor detection rate was taken as a threshold for discarding participants who were suspected to not have paid sufficient attention to the exposure stream. Any participants who detected less than 60% of distractors were discarded from subsequent analyses. On average, participants detected 96.57% of distractors (SD = 0.06). No participant detected less than 60% of distractors, and the average response time was 396.19 msec (SD = 0.03). Based on these results, all participants were retained for subsequent analyses.

Process Dissociation Procedure

Two-AFC data was analysed separately under inclusion and exclusion instructions for the purpose of the PDP. The proportion of training sequences chosen was at chance (0.5) under inclusion conditions (M = 0.54, SD = 0.13), $t(24)$ = 1.549, p = .067, one-tailed, 95% CIs [-0.029 0.112], Cohen’s d = 0.310 and at chance under exclusion conditions (M = 0.49, SD = 0.12), $t(23)$ = -0.326, p = 0.747, two-tailed, 95% CIs [-0.070 0.056], Cohen’s d = -0.067. This indicated that participants had not acquired any knowledge of the triplet structure in this experiment or failed to express this knowledge through the 2AFC task. This was further reinforced by a paired-samples t-test showing that there was no significant difference in the proportion of training triplets chosen under inclusion and exclusion, $t(23) = 1.07$, $p = .296$, two-tailed, 95% CIs of the difference [-0.045 0.141], Cohen's $d = 0.218$. For a dot plot of inclusion performance, refer to Figure 6.1. From this, it is evident that the majority of our participants in this experiment performed around chance level.

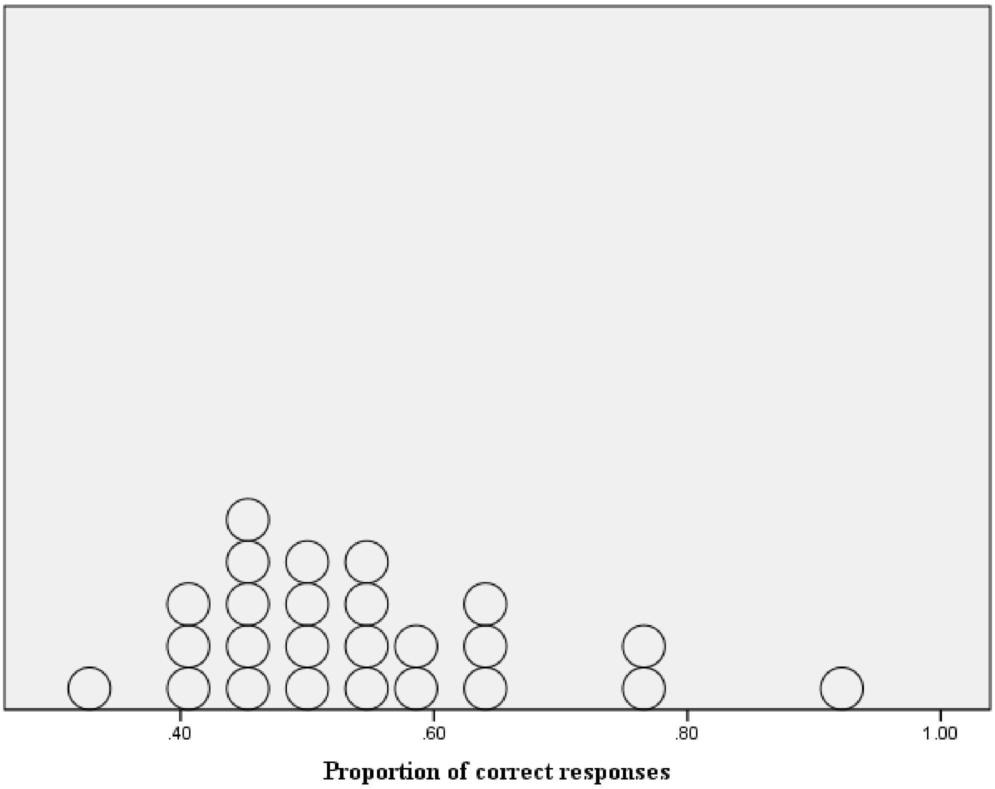

Figure 6.1: Simple dot plot of participants' performance in the 2AFC task, representing each individual's proportion of correct responses.

Guessing and zero correlation criteria

To evaluate whether participants used one type of knowledge attribution in particular, two paired-samples t-tests, one for inclusion and one for exclusion, were carried out between the proportion of guess and memory attributions. We found that, under inclusion, significantly more guess ($M = 0.62$ $SD = 0.24$) than memory ($M = 0.38$ $SD = 0.25$) attributions were used, $t(24) = 2.336$, $p = .028$, two-tailed, 95% CIs of the difference [0.026 0.045], Cohen's $d = 0.507$. Similarly, the proportion of guess attributions under exclusion ($M = 0.63$ $SD = 0.26$) was significantly higher than the proportion of memory attributions ($M = 0.36$ $SD = 026$), $t(23) = 2.537$, $p = .018$, two-tailed, 95% CIs of the difference [0.049 0.486], Cohen's $d = 0.518$. See Figure 6.2 for t-test results.

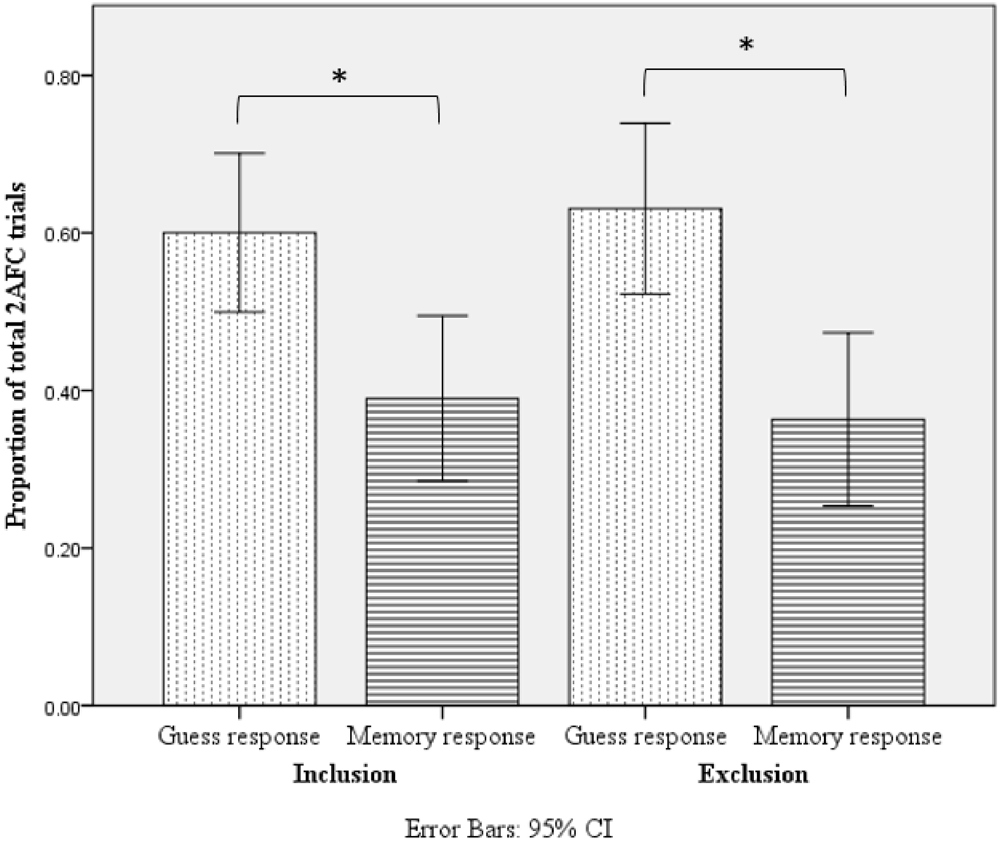

Figure 6.2: Proportion of 2AFC trials out of total in which guess and memory attributions were used, separately for inclusion and exclusion conditions. Significant t-test results are marked with one asterisk (*).

For the purpose of the guessing criterion, the proportion of correct responses in trials in which participants were guessing, using their intuition or their memory was compared separately to chance (0.5). This analysis was carried out for both inclusion and exclusion instructions (Table 6.1). Participants performed at chance under each type of knowledge attribution, under both inclusion and exclusion, with the exception of guessing under inclusion. In fact, performance was significantly above chance when participants were guessing. This, according to the guessing criterion, is indicative of implicit knowledge. However, it is important to note that the large majority of knowledge attributions were guesses, and therefore the analysis of guessing attributions had more statistical power that the analysis of remember attributions. Therefore, caution must be used when interpreting these results in favour of implicit knowledge. See Table 6.1 for a summary of the guessing criterion results.

PDP condition	Knowledge attribution	*N*	Mean (*SD*)	*t*	df	*p*	Cohen's *d*
Inclusion	**Guess**	25	0.54 (0.11)	1.820	24	.041*	0.364
	Memory	24	0.53 (0.24)	.578	23	.285	0.118
Exclusion	**Guess**	24	0.51 (0.09)	.631	23	.534	0.129
	Memory	22	0.46 (0.27)	-.666	21	.513	-0.142

Table 6.1: One-sample t-tests comparing the proportion of correct responses for each of the three knowledge attributions to chance level (0.5) – guessing criterion. Results are displayed separately for inclusion and exclusion conditions. Significant p-values are marked with one asterisk (*) for significance at the 0.05 level and two asterisks (**) for significance at the 0.01 level. Results for inclusion are one-tailed.

A paired-samples t-test was carried out between confidence in trials in which participants were correct and in which they were wrong for the purpose of the zero correlation criterion. As can be seen in Table 6.2, none of the results, in either inclusion or exclusion, were significant, with very similar confidence ratings in correct and wrong trials, suggesting that participants were not able to track their knowledge.

PDP condition	Response correctness	*N*	Mean (*SD*)	*t*	df	*p* (*2-tailed)*	Cohen's *d*	95% CIs of the difference
Inclusion	**Correct**	25	62.81 (7.60)	1.282	24	.212	0.256	[-0.668 2.857]
	Incorrect	25	61.72 (6.76)					
Exclusion	**Correct**	24	61.26 (7.13)	-1.315	23	.202	-0.268	[-3.042 0.678]
	Incorrect	24	62.45 (8.89)					

Table 6.2: Results of paired-samples t-tests comparing confidence in trials when participants were correct and when they were incorrect (guessing criterion). Results are displayed separately for inclusion and exclusion conditions. Significant p-values are marked with one asterisk (*) for significance at the 0.05 level and two asterisks (**) for significance at the 0.01 level.

Triplet Preference Analysis

Our triplet preference analysis aimed to assess participant biases towards specific triplets. For this purpose, we carried out a one-way repeated-measures ANOVA on the number of times that each of the four triplets from L1 and from L2 was chosen under inclusion, regardless of correctness. There was a significant main effect of triplet type for L1 triplets, $F(3, 72) = 4.678$, $p = .005$, $\eta_p^2 = 0.163$. Pairwise comparisons showed that this was driven by a significant difference between triplet 2 and 3 ($p = .018$) (Figure 6.3). The effect of triplet type for L2 triplets was non-significant, $F(3, 72) = 0.917$, $p = .437$, $\eta_p^2 = 0.037$.

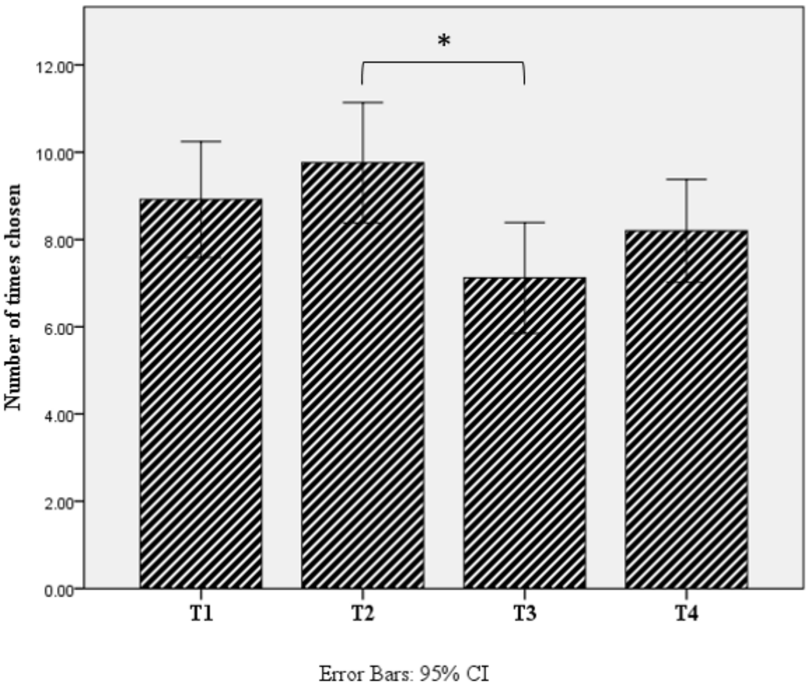

Figure 6.3: Average number of times each of the triplets in L1 was chosen under inclusion. Note: the maximum number of times each individual triplet could be chosen was 16, as each triplet was repeated 16 times within the test phase. Significant differences between triplets as detected by pairwise comparisons are marked with an asterisk.

Rapid Serial Visual Presentation (RSVP) task

In our analysis of the RSVP data, we defined a time window for correct response from 150 msec post target presentation to 900 msec post target presentation, which implies that participants had 750 msec to make a response. With this approach, we aimed to maximise the time that participants had to make a response, at the same time ensuring that there was no overlap between consecutive time windows. Any response provided faster than 150 msec post target onset was considered too fast to belong to that target, and was therefore considered wrong. If two responses were provided by the participant after target presentation, this was taken as self-correction, and only the second response was considered for analysis.

In the same was as our behavioural RSVP analysis, we averaged all correct response times to target shapes in first, second and third position within a triplet. It is worth noting that, as each test stream was concatenated with itself in each trial, and therefore there could be as many as two response times per trial, provided that both responses were correct, more data points contributed to our averages in this version of the RSVP than in Chapter 4.

We used a one-way repeated-measures ANOVA to compare response times to target shapes in first, second and third position within triplets. This showed no effect of shape position, $F(2,48)= 0.64$, $p= .532$, $\eta^2_p= 0.026$. Similarly, there was no significant effect of shape position on accuracy, $F(1.613, 38.71) = 3.475$, $p = .050$, $\eta^2_p = 0.126$ (Greenhouse-Geisser corrected). Descriptive statistics for the RSVP task can be found in Table 6.3.

Performance measure	Shape position	Mean (SE)	95% CIs around the mean
RTs (msec)	First	313.71 (9.17)	[294.783 332.628]
	Second	314.62 (6.51)	[301.183 328.056]
	Third	309.01 (7.51)	[293.522 324.501]
Percentage Correct	First	93.38 (1.51)	[90.252 96.498]
	Second	94.50 (2.32)	[89.713 99.287]
	Third	90.00 (1.53)	[86.840 93.160]

Table 6.3: Descriptive statistics for RSVP task performance

Analysis of learners

Given that the majority of participants in this experiment performed around chance, we were interested in comparing these results to results in a subset of good performers. In the present task, the proportion of correct responses needed by each participant to perform individually above chance was 0.61[6]. Using this criterion, we identified a sample size of six good performers.

Process Dissociation Procedure

The learners, when isolated from the pooled sample, performed significantly above chance (0.5) under inclusion, $t(5) = 4.969$, $p = .002$, one-tailed, 95% CIs [0.111 0.347], Cohen's $d = 2.029$, choosing an average proportion of training triplets of 0.73 ($SD = 0.11$), which indicates that they had acquired sufficient knowledge of the triplets to perform well in the 2AFC task. However, their performance under exclusion conditions was at chance, $t(5) = -1.647$, $p = .161$, one-tailed, 95% CIs [-0.222 0.045], Cohen's $d = -0.672$, with an average proportion of training triplets chosen of 0.41 ($SD = 0.13$). This could indicate implicit knowledge.

Guessing and zero correlation criteria

The proportion of correct responses was significantly above chance for both guess ($p = .007$, one-tailed) and memory ($p = .006$, one-tailed) under inclusion, which may suggest the presence of some implicit knowledge in this group. However, when separated into guess and memory attributions, the proportion of correct responses under exclusion did not reach significance in either (all ps > .068). Confidence when correct ($M = 70.02$ $SD = 5.82$) was significantly higher than confidence when wrong ($M = 63.44$, $SD = 6.41$) under inclusion ($p = .028$, two-tailed), indicating explicit knowledge by the zero-correlation criterion. However, no significant difference between the two ($p = .712$, two-tailed) was observed under exclusion.

Rapid Serial Visual Presentation Task

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[6] In the same way as for Chapter 5, the threshold for individual above-chance performance was arrived at using the binomial distribution to obtain information on the probability of obtaining any one outcome and, through use of the cumulative distribution function, the probability of obtaining any outcome below or above a certain number of trials. Therefore, in order to compute, in MATLAB, the minimum number of correct trials required to be above chance for a one-tailed outcome, we used the following formula: N = 64; c = 2; L2 = binoinv(0.95,N,1/c), where N is the number of trials, 32 in the case of our 2AFC task, c is the number of choices per trials, based on only one correct choice in our 2AFC task, L2 is a vector containing the limit for above chance performance. A 5% alpha rate was used.

The group of good performers also showed a non-significant effect of target position on RTs $F(2, 10) = 0.892$, $p = .004$, $\eta^2_p = 0.151$, and on correctness $F(2, 10) = 0.284$, $p = .758$, $\eta^2_p = 0.054$, showing that their knowledge of the shape triplets, which they could express in the 2AFC task could not be expressed in the RSVP task.

6.3.2 ERP results

ERP Data analysis

Our statistical analysis focused on mean ERP amplitudes for our components of interest. We defined time windows for these on the basis of both previous research and visual inspection of the ERPs.

6.3.2.1 Exposure phase

For the analysis of the exposure data, we focused on the P1, N1 and N400 components, based on a combination of visual inspection and the results obtained by previous literature which has used a visual and auditory triplet learning paradigm. Our choice of the N1 and N400 was determined by their association with the "triplet onset effect" (Abla et al., 2008; Abla & Okanoya, 2009; Mandikal Vasuki et al., 2017). Therefore, these components were of interest for the detection of a learning effect in the ERPs. Upon visual inspection of our data, a clear P1 component was evident at occipital and posterior sites, which motivated our decision to include it as part of the exposure analyses.

For the purpose of our ERP analysis, we split the exposure stream into two halves (here referred to as "sections"). This is because we expected any effects related to learning of the visual triplets to be more prominent in the second than first half of exposure, and therefore we were interested in comparing ERPs between the two halves. We used a three-way mixed ANOVA on mean amplitude for our electrodes of interest with Learning (learners, non-learners) as the between-subjects factor, and Section (section 1, section 2) and Shape (position 1, position 2, position 3) as the within-subjects factors. This aimed to assess effects of learning, by comparing participants categorised as "learners" to the ones categorised as "non-learners", to compare the first and second half of the exposure phase, given that learning is thought to become more manifest in the second half of exposure, and, finally, to assess the effects of triplet learning and segmentation by comparing shapes in first, second and third position within a triplet.

P1 time window (70-130 msec)

Based on visual inspection of the data, the P1 component appeared more evidently at occipital and posterior sites (Figure 6.4), therefore our analysis focused on PO7, PO3, O1, PO8, PO4 and O2.

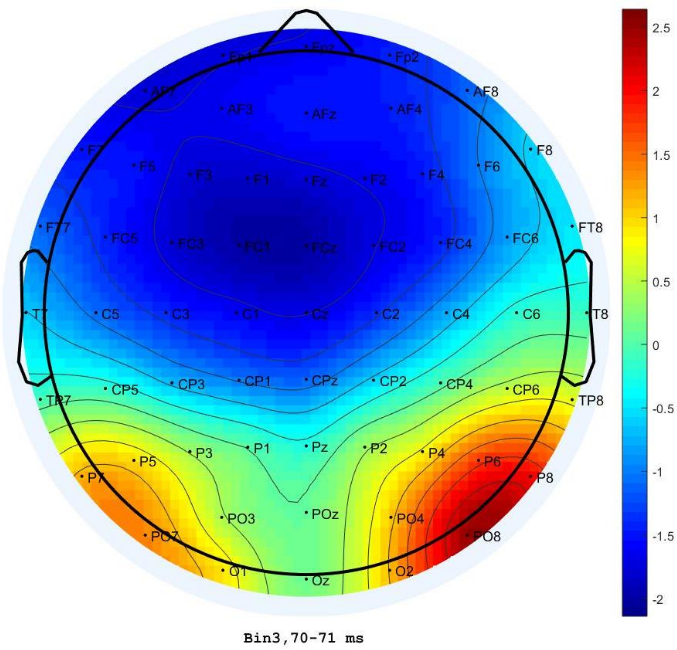

Figure 6.4: Topographic distribution of the P1 mean amplitude within the 70-130 msec time window for shapes in position 3 within a triplet.

Our Learning x Section x Shape mixed ANOVA identified a main effect of Shape Position, which was consistent across all electrodes of interest, as well as a main effect of Section, which was also consistent across all electrodes of interest, except for PO3. In addition to this, a significant interaction between Shape Position and Learning was found at sites PO7 and O1, therefore these electrodes were pooled for analysis.

In this new analysis, the main effect of Section was statistically significant, F (1, 23) = 9.136, p = .006, $\eta_p^2 = 0.284$, with higher amplitude in section 1 (M = 3.19 SE = 0.43) than section 2 (M = 2.42 SE = 0.39). There was also a significant main effect of Shape Position, F (2, 46) = 17.976, p < .001,

$\eta_p^2 = 0.439$. Pairwise comparisons showed that P1 amplitude was significantly reduced for shapes in position 3 compared to shapes in position 1 ($p = .047$) and in position 2 ($p < .001$). Amplitude for shapes in position 1 was also significantly reduced compared to shapes in position 2 ($p = .002$), which had the highest P1 amplitude. The reduced P1 amplitude to shapes in position 3 within a triplet could potentially be an index of predictability, representing the higher predictability of shapes in position 2 and 3 compared to shapes in position 1.

We also found a significant interaction between Learning and Shape Position, F (2, 46) = 3.949, $p = .026$, $\eta_p^2 = 0.147$ (Figure 6.5).

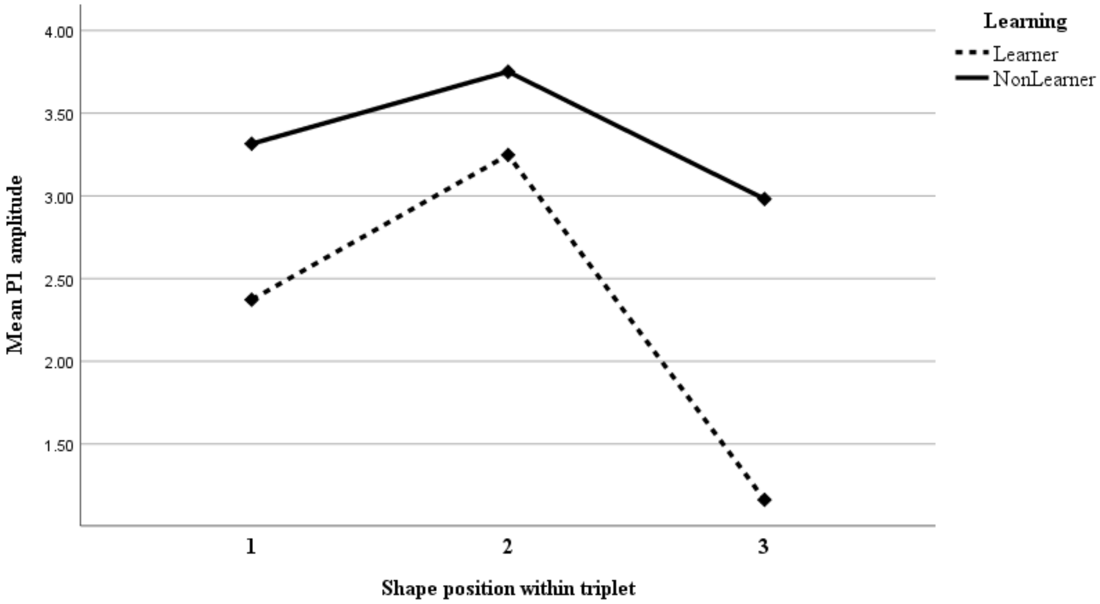

Figure 6.5: Significant Learning x ShapePosition interaction on mean P1 amplitude at O1 and PO7 sites merged.

In order to post-hoc this effect, we carried out three independent-samples t-tests between learners and non-learners separately for each shape position. Despite the mean difference between learners and non-learners was larger for shapes in position 3 ($M = 1.82$, $SE = 0.94$) than shapes in position 2 ($M = 0.50$, $SE = 0.80$) and position 1 ($M = 0.94$, $SE = 0.71$), none of the Bonferroni-corrected post-hoc t-tests were significant (all Bonferroni-corrected ps > .192). To further investigate the differences in mean amplitude to the three shape positions between learners and non-learners, we also carried out two one-way repeated-measures ANOVAs with factor Shape, separately for learners and non-learners. The main effect of Shape was significant for both learners, $F(2, 10) = 6.867$, $p = .013$, $\eta_p^2 = 0.579$ and non-learners, $F(2, 36) = 7.150$, $p = .002$, $\eta_p^2 = 0.284$. Pairwise comparisons showed that P1 amplitude was significantly reduced for shapes in position 1 than shapes in position 2 for learners ($p = .048$). However, this difference was not significant for non-learners ($p = .053$). The reduced mean P1 amplitude to shapes in position 1 than shapes in position 2, the first predictable shapes within one triplet, could be an ERP index of a learning effect, which would be supported by the fact that this difference is significant in learners but not in non-learners. There was no significant difference between shapes in position 1 and shapes in position 3 for either learners ($p = .477$) or non-learners ($p = .575$). Shapes in position 3 had reduced amplitude compared to shapes in position 2 in both learners and non-learners, but this difference was only significant in the non-learners ($p = .002$), with $p = .054$ in the learners. The reduced amplitude for shapes in position 3 could also potentially be an index of learning. It is therefore surprising that this effect is non-significant in learners. We suggest that this could be due to the small sample size in this group and that, given that the effect was approaching significance ($p = .054$), a positive result might be found in future investigations with a larger sample size. In the non-learners, this finding is potentially of high interest, as it could be seen as indexing implicit knowledge which could not be detected behaviourally through the 2AFC task. Future research should aim to clarify these findings further, using more even sample sizes in learners and non-learners, specifically aiming to compare the differences in mean P1 amplitude for the different shape positions within a triplet for learners and non-learners. Grand average ERPs for the Learning x ShapePosition interaction are displayed in Figures 6.6 to 6.9.

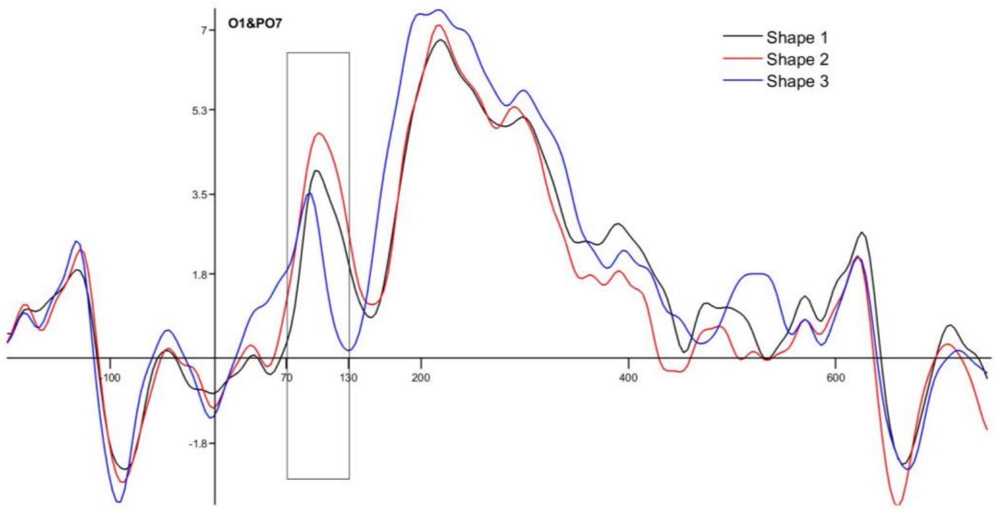

Figure 6.6: Mean P1 amplitude for shapes in position 1, 2 and 3 within a triplet for learners in the first half of exposure (section 1) at the pooled O1 and PO7 sites. The rectangle contains our P1 time window (70-130 msec).

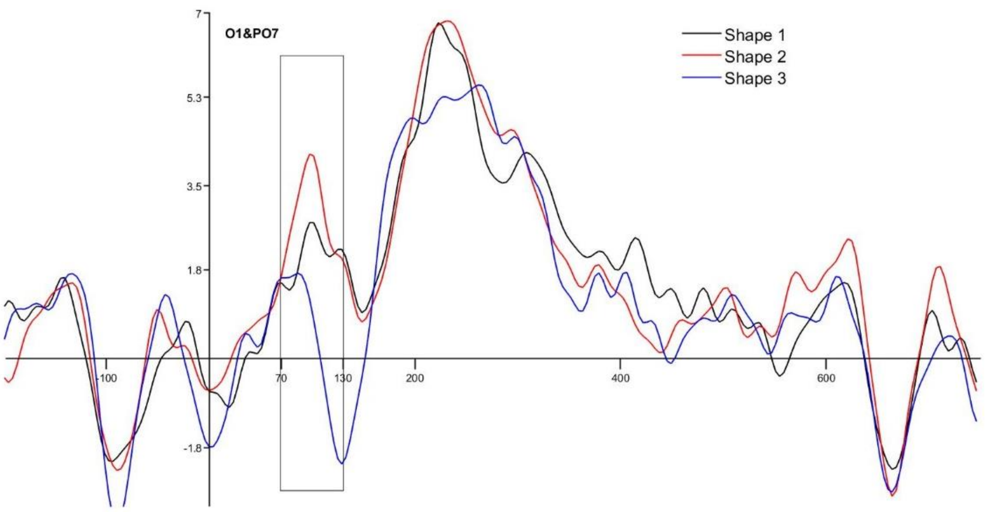

Figure 6.7: Mean P1 amplitude for shapes in position 1, 2 and 3 within a triplet for learners in the second half of exposure (section 2) at the pooled O1 and PO7 sites. The rectangle contains our P1 time window (70-130 msec).

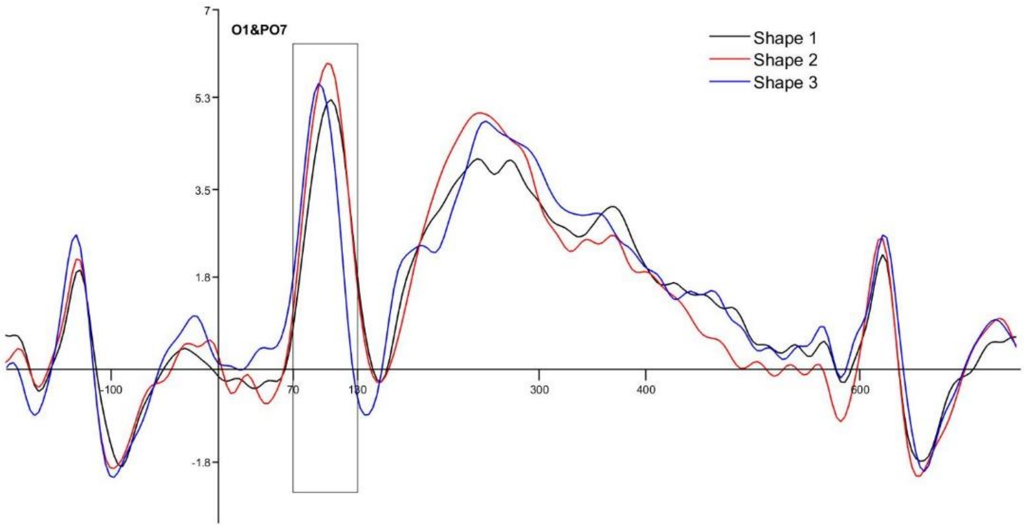

Figure 6.8: Mean P1 amplitude for shapes in position 1, 2 and 3 within a triplet for non- learners in the first half of exposure (section 1) at the pooled O1 and PO7 sites. The rectangle contains our P1 time window (70-130 msec).

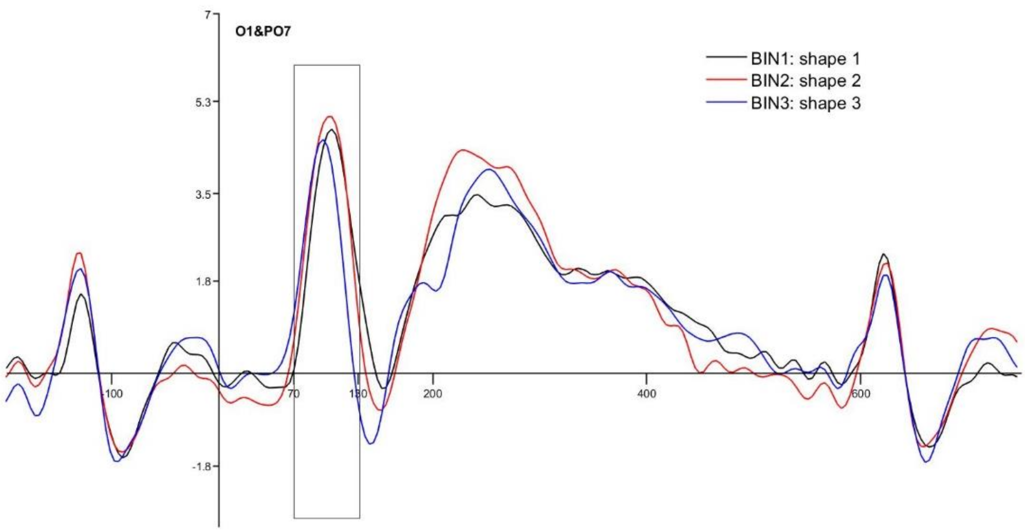

Figure 6.9: Mean P1 amplitude for shapes in position 1, 2 and 3 within a triplet for non-learners in the second half of exposure (section 2) at the pooled O1 and PO7 sites. The rectangle contains the P1 time window (70-130 msec).

N1 time window (90- 150 msec)

Our analysis of the N1 component was focused around central sites C2, C4, C5, C6, C1 and C3. This was based on previous findings of the N1 related to the triplet onset effect showing a larger negativity at central, and frontal, scalp locations (Abla et al., 2008), which was also confirmed through visual inspection in our data (Figure 6.10).

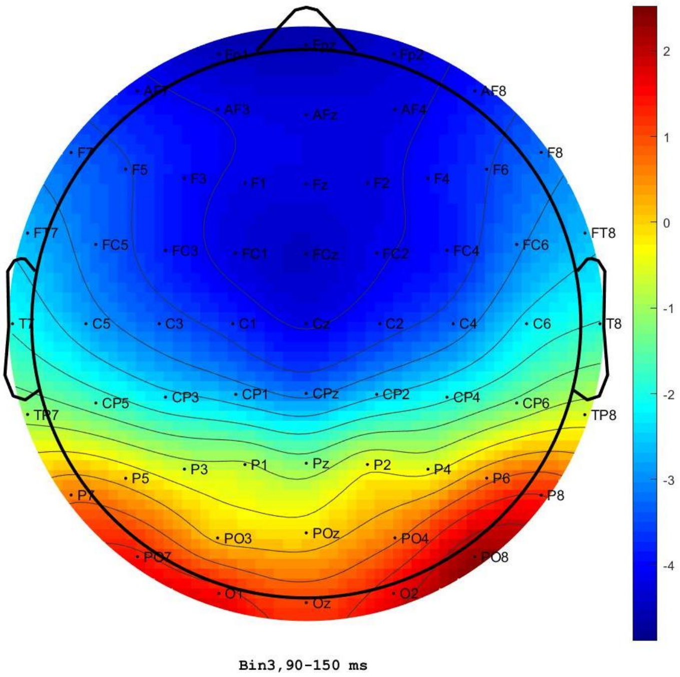

Figure 6.10: Topographic distribution of the N1 mean amplitude within the 90-150 msec time window for shapes in position 3 within a triplet.

At C3 there was a significant main effect of Shape, $F(2, 44) = 11.162$, $p < .001$, $\eta_p^2 = 0.337$. Pairwise comparisons showed that N1 mean amplitude for shapes in position 1 was significantly higher (more negative) than for shapes in position 2 ($p = .024$) and 3 ($p = .001$). There was no significant difference between shapes in position 1 and shapes in position 3 ($p = .127$) (Figure 6.11). The finding of smallest N1 amplitude for shapes in position 3 mirrors our P1 findings of reduced amplitude for shapes in this position. The Shape main effect was consistent in our analyses at all sites of interest. No other significant effects were found in this analysis.

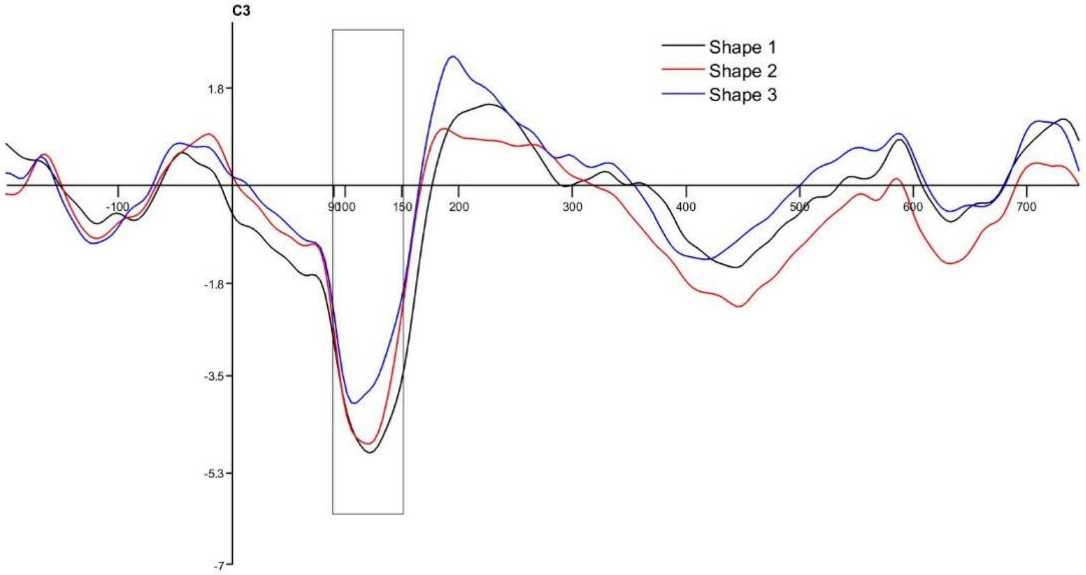

Figure 6.11: Plot of exposure data averaged across learners and non-learners, and exposure section showing the main effect of Shape on mean N1 amplitude. The rectangle contains the N1 time window (90-150 msec).

N400 time window (350-500 msec)

The same sites of interest as for N1 were used for our analysis of the N400 component: C2, C4, C5, C6, C1 and C3. The choice of central sites was, again, motivated by previous findings of an N400 related to the triplet onset effect and more evident at central locations (Abla & Okanoya, 2009). This scalp distribution for the N400 was also confirmed through visual inspection of our data (Figure 6.12).

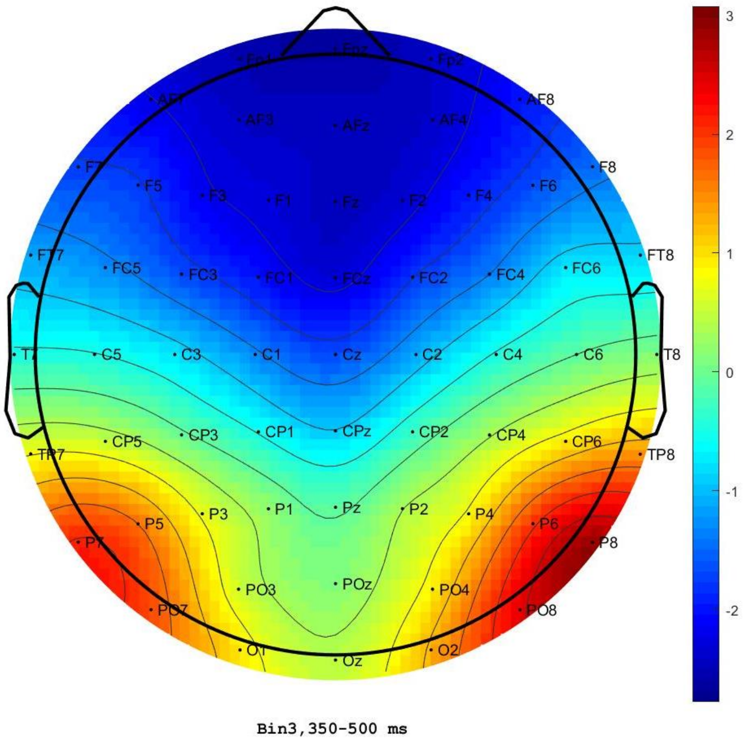

Figure 6.12: Topographic distribution of the N400 mean amplitude within the 350-500 msec time window for shapes in position 3 within a triplet.

Similarly to our analysis of the N1 component, our three-way mixed ANOVA found a significant main effect of Shape at C3, $F(2, 44) = 11.870$, $p < .001$, $\eta_p^2 = 0.350$. Pairwise comparisons revealed that the mean N400 amplitude for shapes in position 2 was significantly higher (more negative) than for shapes in position 1 ($p = .001$) and in position 3 ($p < .001$). There was no significant difference between shapes in position 3 and 2 ($p = 1.000$) (Figure 6.13).

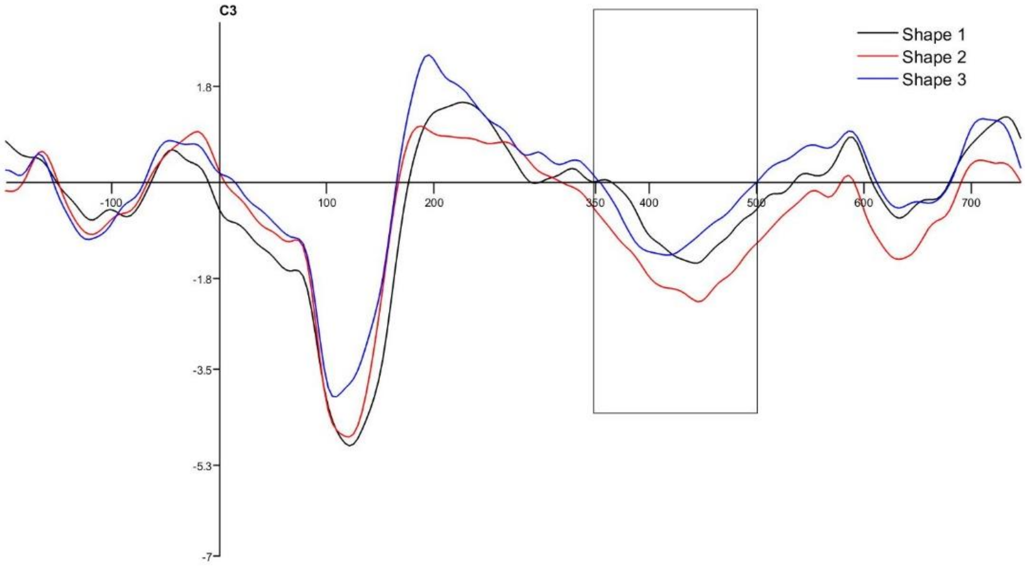

Figure 6.13: Plot of exposure data averaged across learners and non-learners, and exposure section showing the main effect of Shape on mean N400 amplitude. The rectangle contains the N400 time window (350-500 msec).

Our analyses of all sites of interest for this component show that the higher mean amplitude of shapes in position 2 was a consistent effect. This main effect of Shape, however, was not related to learning. In fact, there was no Shape x Learning interaction (p = .437). As this effect is highly relevant for our research question, future studies should investigate it further, using a larger sample of learners to see whether, in the same way as for the P1 component in the present study, any differences between learners are observed in mean amplitudes to shapes in first, second and third position.

The main effect of Section was also non-significant, as well as the Section x Learning interaction and three-way interaction of Shape x Section x Learning. However, there was a significant Section x Shape interaction, $F(2, 44) = 5.430$, $p = .008$, $\eta_p^2 = 0.198$. This was present for half of the sites of interest: C3, C1 and C2 but not at C4, C5 and C6. Shapes in position 2 had the highest amplitude of the three shapes, in both section 1 and section 2. However, higher mean amplitude was found in section 1 than section 2 for shapes in position 1 and position 2 but the opposite pattern was observed for shapes in position 3 (Figure 6.14). As post-hoc tests to this interaction, three paired-samples t-tests were carried out between section 1 and section 2 separately for each shape. None of the tests were significant after Bonferroni correction (all Bonferroni-corrected ps> .144).

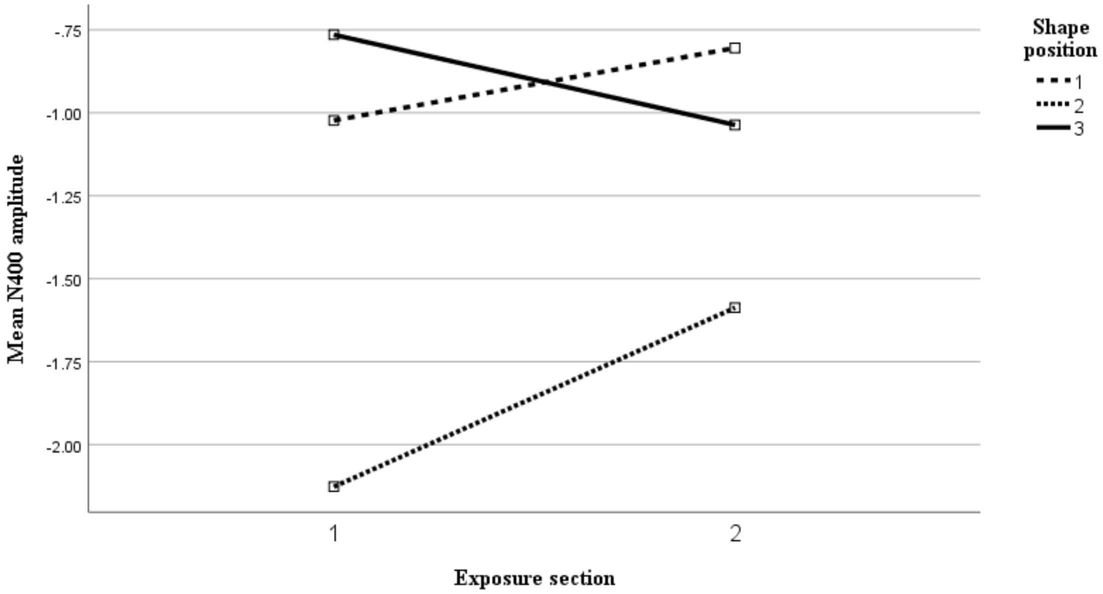

Figure 6.14: Shape x Section interaction at C3 site for the N400 component.

These findings seem to be at odds with Abla & Okanoya's (2009) triplet onset effect, in that the authors also found a difference between shapes in different positions, but the largest N400 amplitude was observed for shapes in position 1, whilst we observed the largest amplitude for shapes in position 2. This is an interesting finding, which may be related to the fact that shapes in position 2 are the first predictable shapes within a triplet.

Analysis of Implicit and explicit knowledge: P3b time window (220-320 msec)

Aiming to analyse ERP differences in explicit and explicit knowledge, we used 2AFC task performance to divide triplets into implicit and explicit. Implicit triplets were triplets that were correctly responded to which had more guess than memory attributions, and explicit triplets were triplets correctly responded to which had more memory than guess attributions. We analysed ERPs time locked, in separate analyses, to the first, second or third shapes within a triplet. It is worth noting that only a small subset of participants was eligible for this analysis, as we could only compare guess and memory attributions within participants if they had used a combination of both. Four participants were eligible in the learners group and four participants in the non-learners group.

Based on previous research in this area (Fu et al., 2013), we focused on the P3b as an index of explicit knowledge, and we were therefore interested in the differences in this component between implicitly and explicitly-learned triplets. Visual inspection of our data showed that the P3b was more prominent at occipital and posterior sites (refer to Figure 6.15 for a scalp distribution of P3b mean amplitude), therefore our sites of interest for this analysis were: PO7, PO3, O1, PO8, PO4, and O2. (Fu et al., 2013) also studied N2 amplitude in their study, however, upon visual inspection, this component was not evident in our data.

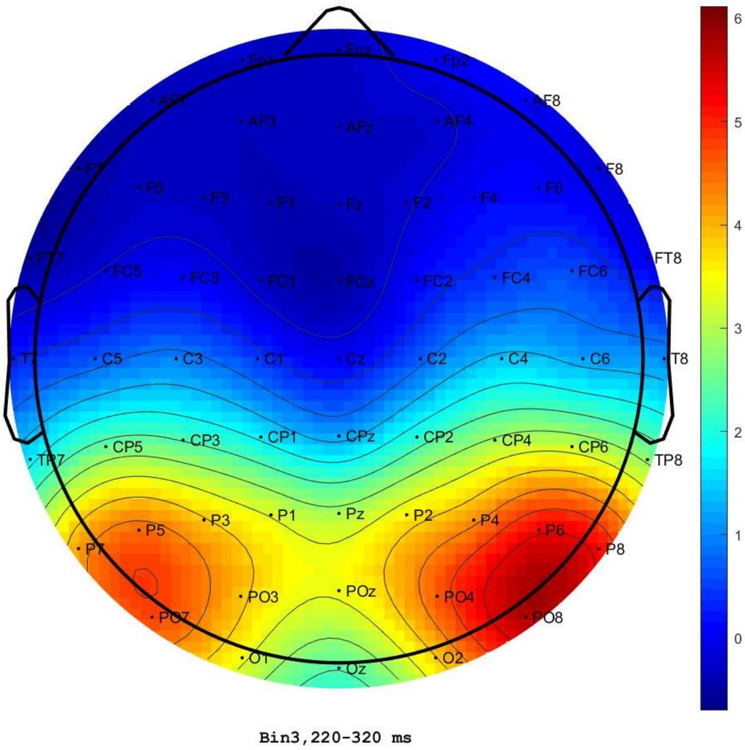

Figure 6.15: Topographic distribution of the P3b mean amplitude within the 220-320 msec time window for shapes in position 3 within a triplet.

Aiming to compare ERPs for guess and memory attributions in learners and non-learners for the first and second section of the exposure phase, we carried out a three-way mixed ANOVA with Section

(section 1, section 2) and Attribution (guess, memory) as the within-subjects factor and Learning (learners, non-learners) as the between-subjects factor. This analysis was carried out separately for shapes in first, second and third position within a triplet.

Our ANOVA results were consistent across most of our sites of interest. We selected PO8 as the most representative site. Our ANOVA on shapes in position 1 found no significant effects. With regards to the main effect of Attribution, comparing guess and memory attributions, and to the Section x Attribution interaction, the lack of significant effects was not surprising for shapes in position 1, as these are the unpredictable shapes within a triplet, therefore we did not expect to observe any differences between implicit and explicit knowledge on these shapes.

For shapes in position 2, at the PO8 site there was a significant main effect of Section, F (1, 6) = 9.137, p = .023, η_p^2 = 0.604, with higher amplitude to the second shape in a triplet in Section 1 (M = 7.72 SE = 0.94) than in Section 2 (M = 6.31 SE = 0.92). Similarly, for shapes in position 3, we found a main effect of Section at PO8, which was consistent across most other electrodes of interest[7], F(1, 6) = 8.334, p = .028, η_p^2 = 0.581, with higher mean P3b amplitude in Section 1 (M = 7.13 SE = 0.90) than in Section 2 (M = 4.81 SE = 0.64). The main effect of Attribution, as well as the Attribution x Section interaction, were not significant for either shapes in position 2 or 3. For grand average ERPs for guess and memory responses, shown separately for our four learners and four non-learners who were eligible for this analysis, see figures 6.17 to 6.20.

[7] For shapes in position 3, a main effect of Section was present at sites: PO7, PO3, O1, PO8, O2.

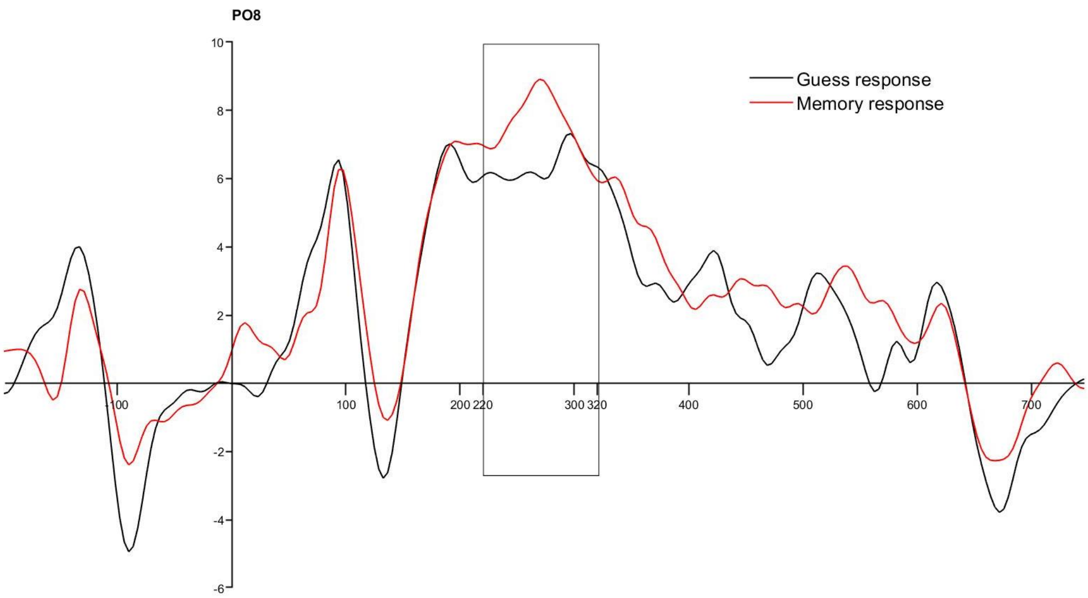

Figure 6.16: Grand average ERPs time-locked to shapes in position 3 for guess and memory responses in learners in the first half of exposure at PO8. The rectangle contains the P3b time window (220-320 msec).

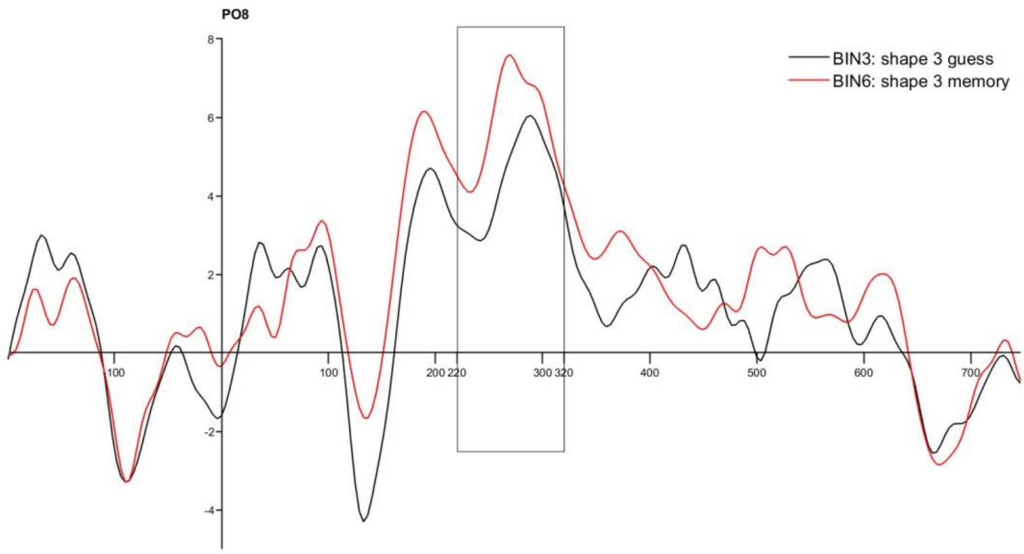

Figure 6.17: Grand average ERPs time-locked to shapes in position 3 for guess and memory responses in learners in the second half of exposure at PO8. The rectangle contains the P3b time window (220-320 msec).

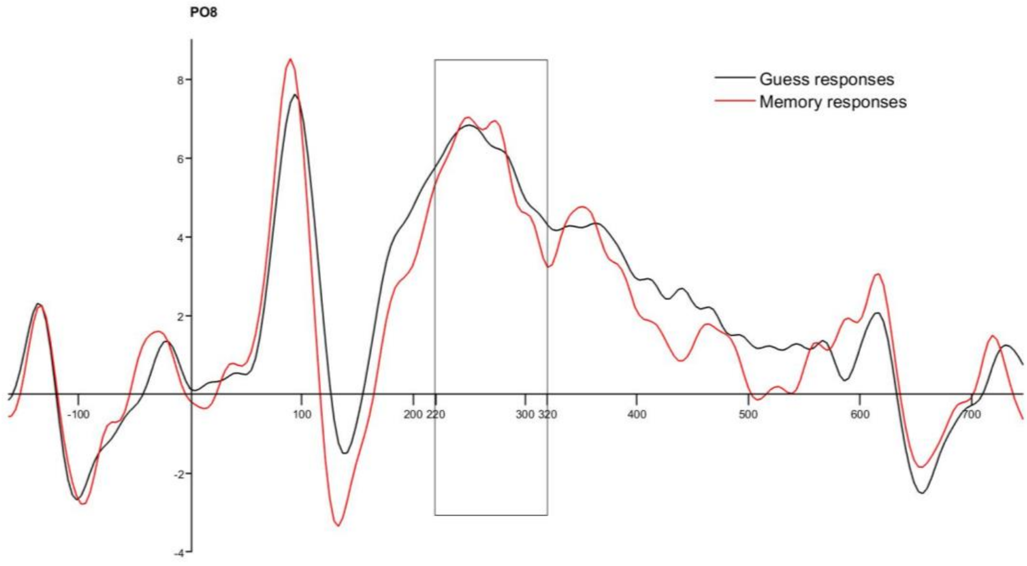

Figure 6.18: Grand average ERPs time-locked to shapes in position 3 for guess and memory responses in non-learners in the first half of exposure at PO8. The rectangle contains the P3b time window (220-320 msec).

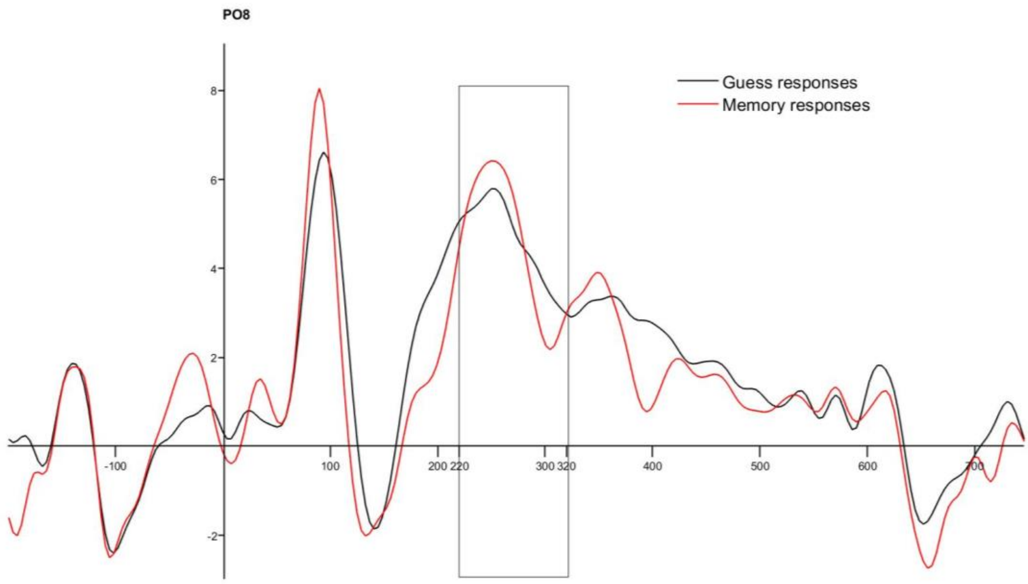

Figure 6.19: Grand average ERPs time-locked to shapes in position 3 for guess and memory responses in learners in the second half of exposure at PO8. The rectangle contains the P3b time window (220-320 msec).

Overall, we found significant effects of Section for shapes in position 2 and 3 within a triplet, reflected in enhanced P3b amplitude in the first compared to the second section of the exposure phase. It is possible that these effects may be due to our participants becoming habituated to the stimuli in the second half of exposure. We found no evidence of a difference in ERP responses between implicit and explicit knowledge attributions, and no evidence that implicit and explicit attributions may be related to learning in our data, as a significant Attribution x Section interaction would have suggested.

6.3.2.2 2AFC Task

Our analysis of ERPs in the 2AFC task focused on a comparison of old and new triplets in the task for the predictable shapes within a triplet: shapes in position 2 and 3. In these analyses we compared components for old and new triplets for learners and non-learners in a 2-way mixed ANOVA: Learning x OldNew.

N400 time window (350-500 msec)

Previous literature (Ferdinand et al., 2010) (Voss & Paller, 2008), has found the FN400 to be an ERP correlate of remembering and familiarity. In our task, familiarity should be reflected in the FN400, which is also referred to as the mid-frontal old/new effect, producing more positive ERPs for old than new items. Based on visual inspection, this component seemed to be present in our data at similar locations as Ferdinand et al's (2010), which they analysed in a very similar time range to the one chosen in the present study, mainly at central and frontal sites, which motivated our choice of central and frontal sites for the analysis of this component: CPz, AFz, Fz, F2, F4 and F6. Our Learning x OldNew ANOVA found no significant effects in the FN400 time window at any of the sites of interest (Figures 6.21 and 6.22).

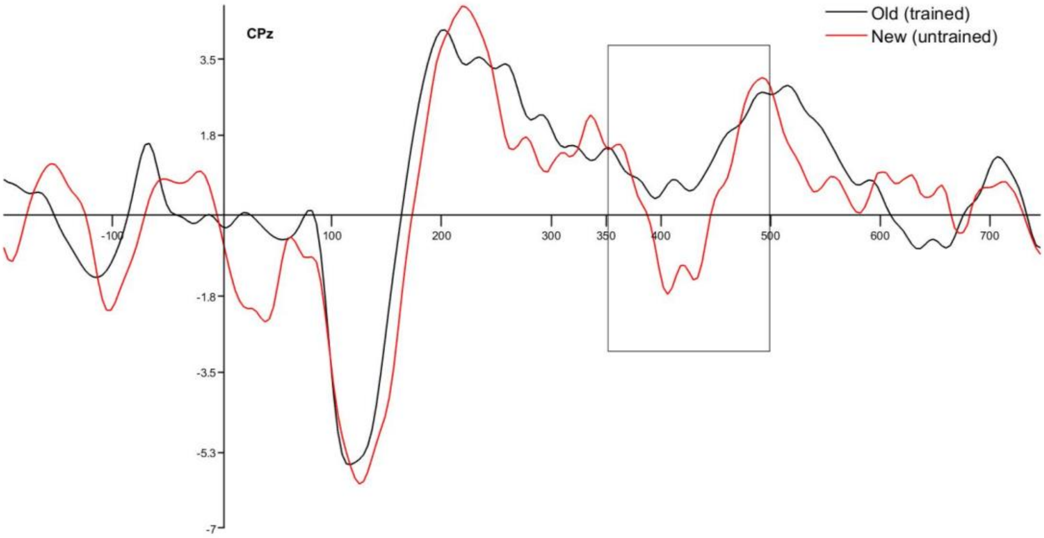

Figure 6.20: Grand average ERPs time-locked to shapes in position 3 for old (trained) and new (untrained) triplets for our group of learners at CPz. The rectangle contains the N400 time window (350-500 msec).

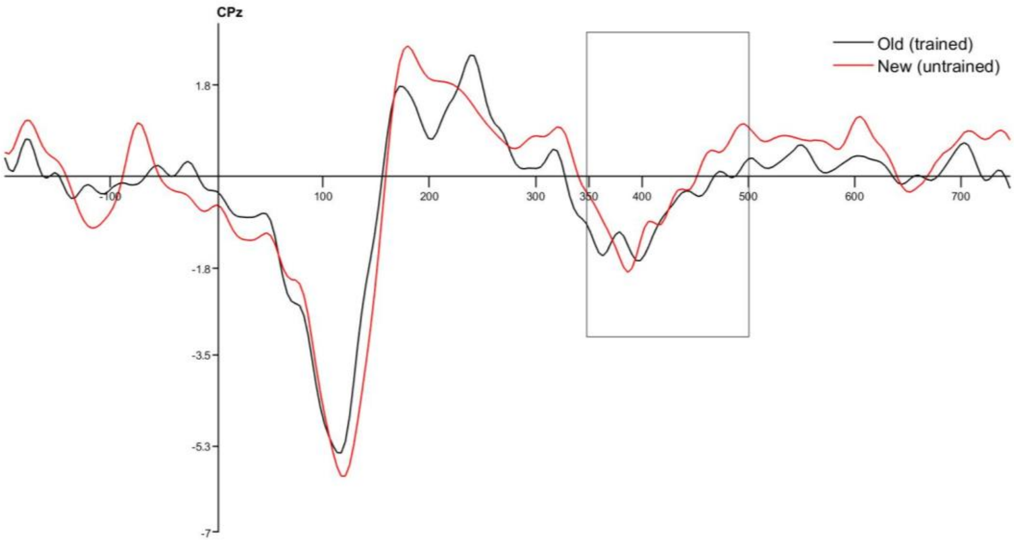

Figure 6.21: Grand average ERPs time-locked to shapes in position 3 for old (trained) and new (untrained) triplets for our group of non-learners at CPz. The rectangle contains the N400 time window (350-500 msec).

N1 time window (90 – 150 msec)

We also focused on the analysis of the N1 component in the same time range as our exposure analysis. In our exposure, we did not find the N1 to be dependent on learning, but found that effects relating to shape position were present. Specifically, we found a higher N1 amplitude for shapes in position 1 within a triplet, an effect which was localised at central sites. Ferdinand et al., (2010) found a difference between verbalisers and non-verbalisers in the N1 component at central sites, despite having used an earlier time window than ours (60-140 msec). Based on their findings, we chose to focus on the N1 component at sites Fpz, AFz, Fz, FCz, Cz, although it is worth noticing that, based on visual inspection, this component in our data was evident at all sites, with a later peak at parietal and occipital sites than at central and frontal sites (Figure 6.23).

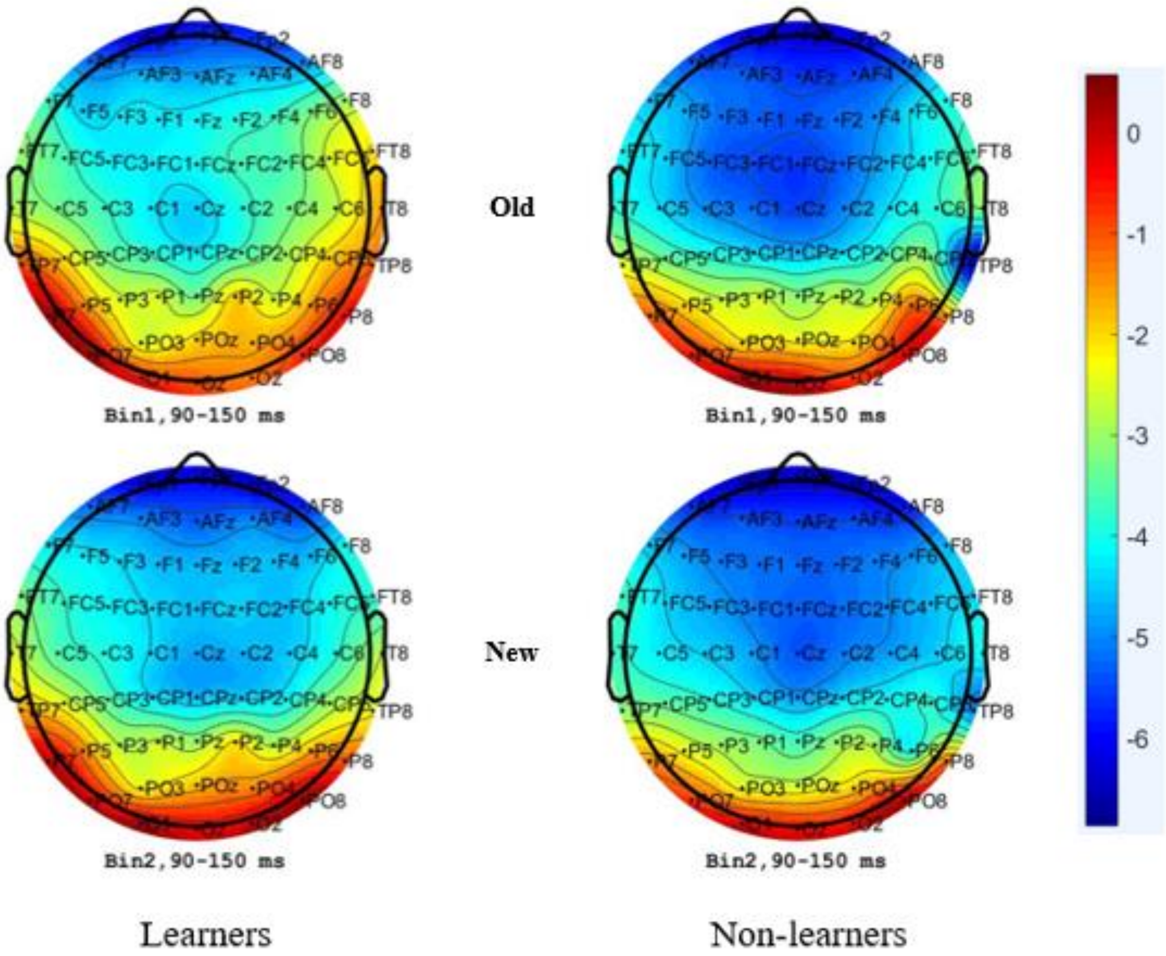

Figure 6.22: Topographic distribution of the N1 mean amplitude within the 90-150 msec time window for shapes in position 3 within old (trained) triplets and new (untrained) triplets for learners and non-learners.

Similar to results relating to our N400 component, our Learning x OldNew ANOVA on N1 mean amplitude found no significant effects at any of our sites of interest. Refer to Figures 6.24 and 6.25 for an illustration of our N1 component for old and new triplets for learners and non-learners.

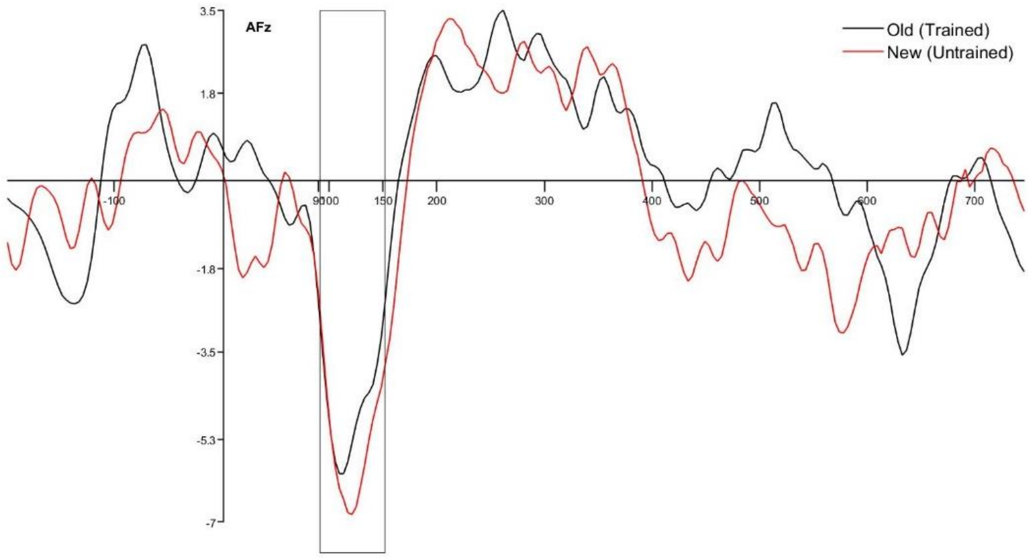

Figure 6.23: Grand average ERPs time-locked to shapes in position 3 for old (trained) and new (untrained) triplets for our group of learners at AFz. The rectangle contains the N1 time window (90-150 msec).

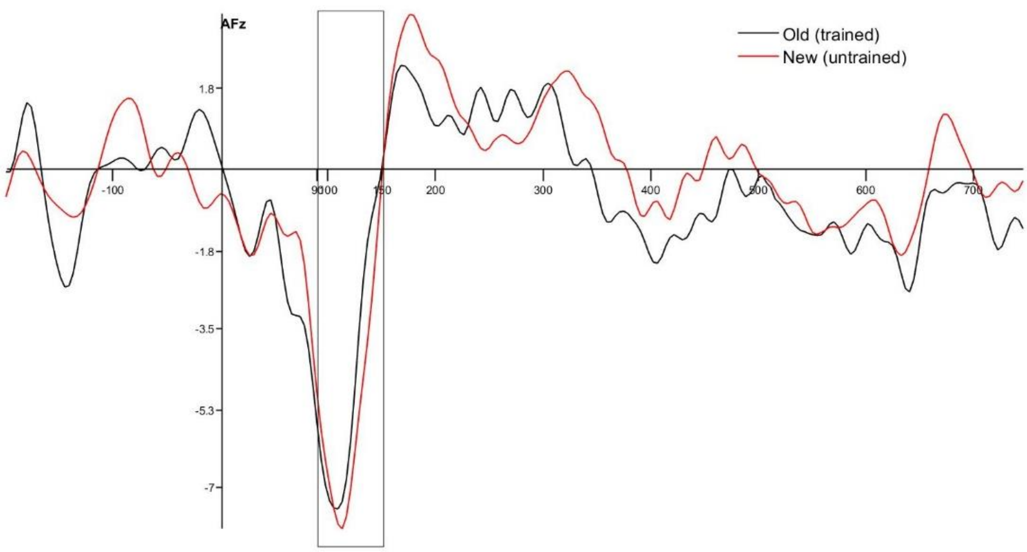

Figure 6.24: Grand average ERPs time-locked to shapes in position 3 for old (trained) and new (untrained) triplets for our group of non-learners at AFz. The rectangle contains the N1 time window (90-150 msec).

P1 time window (70 -130 msec)

Based on visual inspection of our data, a P1 component emerged in the same time range as our exposure phase, which, in exposure, we found to be potentially related to a learning effect. For this reason, in this analysis we carried out the Learning x OldNew ANOVA on the P1 component in the same time range, and at some of the same sites as during exposure (PO7, PO8, PO4, O2).

Our ANOVA showed a main effect of OldNew on P1 mean amplitude at O2, F (1, 23) = 10.208, p = .004, η_p^2 = 0.307, with significantly lower amplitude for shapes in position 3 for an old (M = -2.072, SE = 0.791) than a new (M = -0.816, SE = 0.839) triplet (Figures 6.26 and 6.27). This third-shape effect in P1 is an interesting finding, which could indicate the presence of learning that participants were not aware of. The idea that a learning effect may have been detected in P1 seems to go hand-in-hand with the significant Learning x Shape interaction that we found in the exposure phase. This interesting interpretation, however, would need to be validated by future research using a larger sample size for learners. No other effects on mean P1 amplitude were significant at the O2 site.

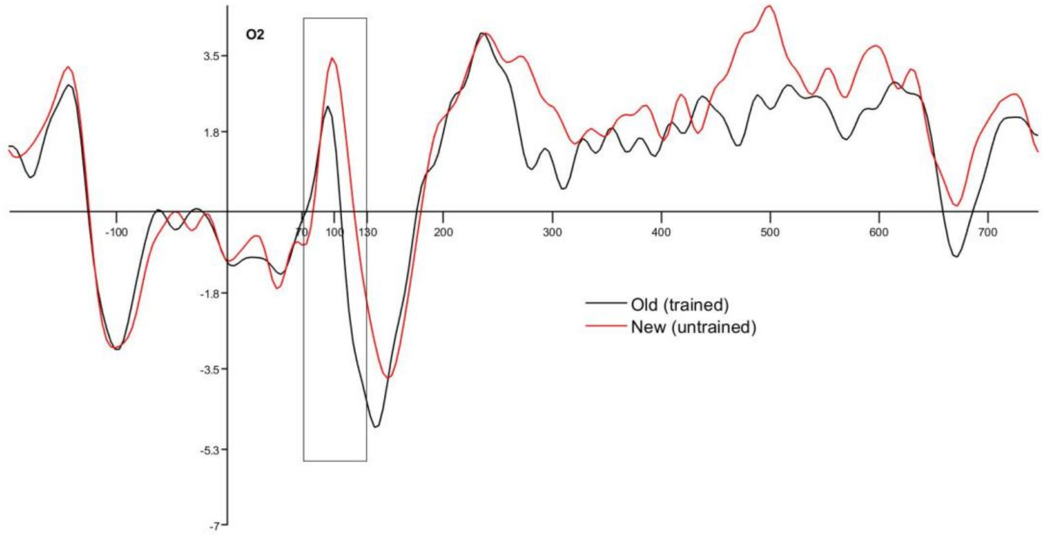

Figure 6.25: Grand average ERPs time-locked to shapes in position 3 for old (trained) and new (untrained) triplets for our group of learners at O2. The rectangle contains the P1 time window (70-130 msec).

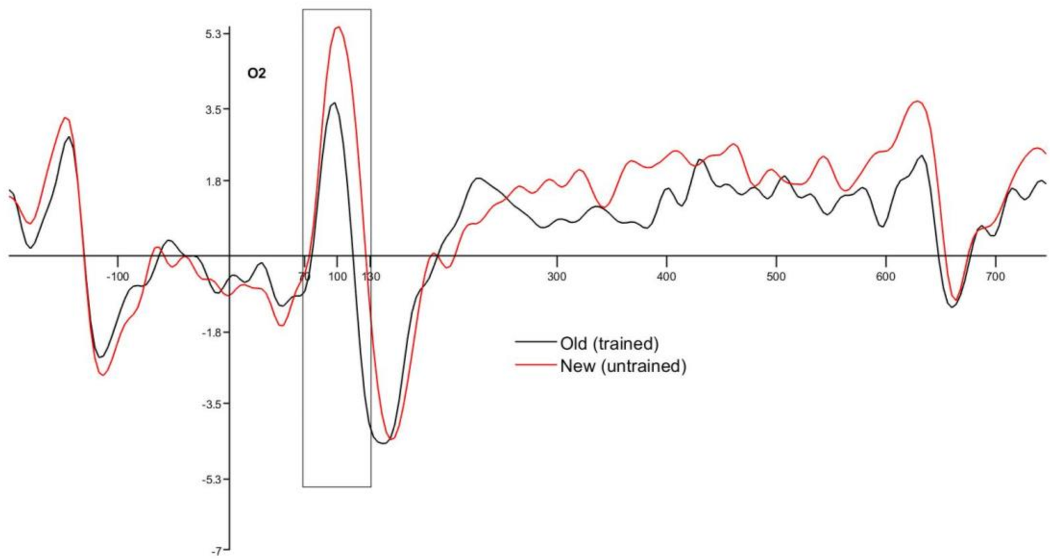

Figure 6.26: Grand average ERPs time-locked to shapes in position 3 for old (trained) and new (untrained) triplets for our group of non-learners at O2. The rectangle contains the P1 time window (70-130 msec).

The old/ new effect present at O2 was also found at PO8, but at no other electrode of interest. There was no effect of Learning and no Learning x OldNew interaction. In fact, as can be seen from Figures 6.26 and 6.27 at O2, the old/ new effect was similar for learners and non-learners.

6.3.2.3 RSVP task

Analysis of targets vs non-targets: P300 time window (300- 500 msec)

We were interested in comparing ERP responses to targets and non-targets in our RSVP task. Based on previous literature (Baldwin & Kutas, 1997) (Trippe, Hewig, Heydel, Hecht, & Miltner, 2007), suggesting a difference in the P300 component between targets and non-targets at sites along the midline, we focused our comparison specifically on the Pz site, at which, amongst other sites, the P300 mean amplitude was maximal (Figure 6.28).

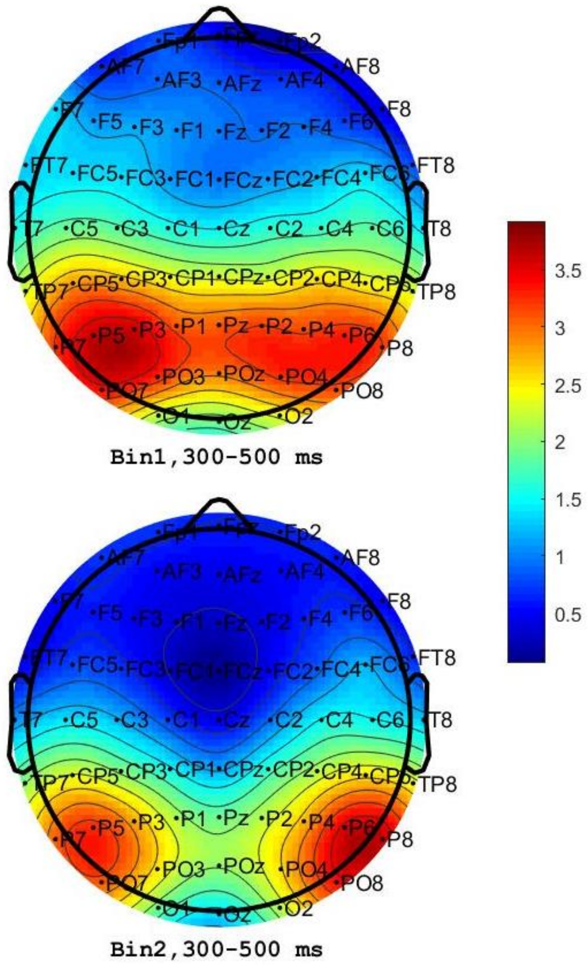

Figure 6.27: Topographic distribution of the P300 mean amplitude within the 300-500 msec time window for targets (shown at the top – Bin 1) and non-targets (shown at the bottom – Bin 2). We chose to represent non-learners for this figure, as an example for the purpose of the P300 scalp distribution, given that the sample size was the highest in this group.

We used a 2-way mixed ANOVA (Learning x Target) to compare ERP responses to target vs non target stimuli in learners and non-learners. We found no main effect of Learning, $F(1, 21) = 2.467$, $p = .131$, $\eta_p^2 = 0.105$, and no Learning x Target interaction $F(1, 21) = 1.462$, $p = .240$, η_p^2 =,0.065, indicating that there were no differences between learners and non-learners in their ERPs in response to target shapes. However, the main effect of Target was significant, $F(1, 21) = 34.691$, $p < .001$, $\eta_p^2 = 0.623$, replicating the well-known effect of a larger P300 for target than non-target items (Baldwin & Kutas, 1997) (Trippe et al., 2007) (Figure 6.29 and 6.30).

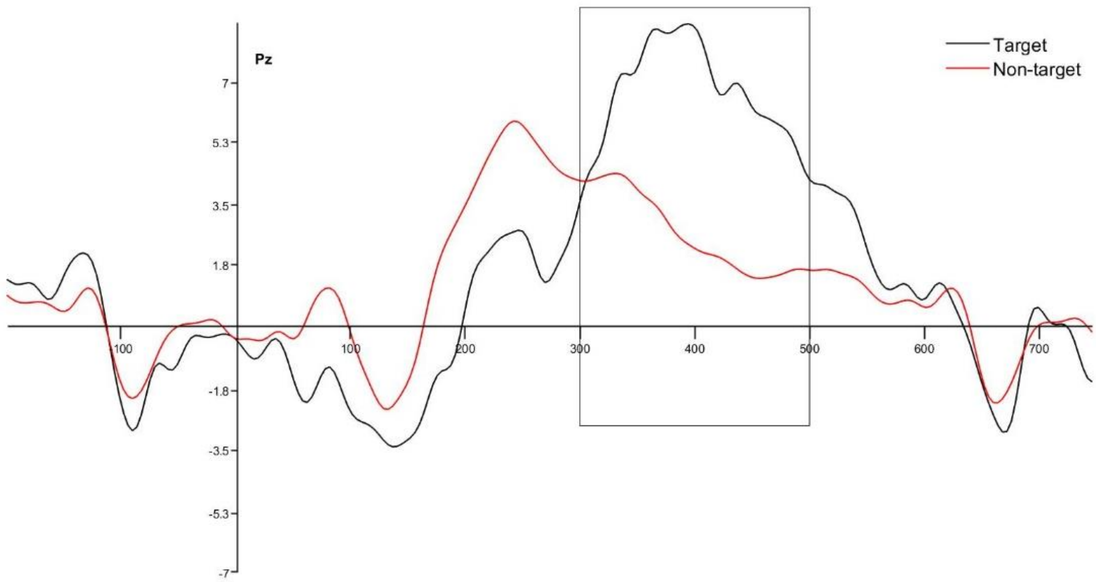

Figure 6.28: Grand average ERPs for targets and non-targets in our group of learners at Pz, showing our P300 difference between the two. The rectangle contains the P300 time window (300-500 msec).

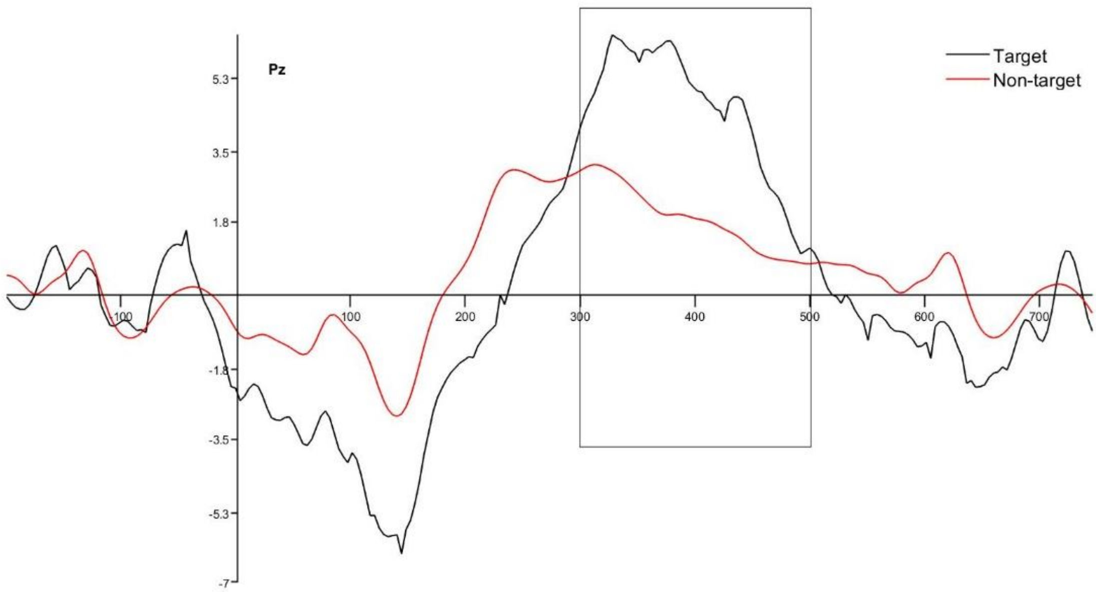

Figure 6.29: *Grand average ERPs for targets and non-targets in our group of non-learners at Pz, showing our P300 difference between the two. The rectangle contains the P300 time window (300-500 msec).*

Analysis of shape position: N1 time window (90-150 msec)

We were also interested in whether the effects observed during exposure with regards to shape position were also observable in the RSVP task. Based on visual inspection of the RSVP data, similarly to exposure, a clear N1 component was present. We therefore analysed this using the same time window as during exposure (90-150 msec), and the same sites of interest: C2, C4, C5, C6, C1 and C3.

In order to compare ERPs for shapes in first, second and third position between learners and non-learners, we carried out a two-way mixed ANOVA with Learning (learners, non-learners) as the between-subjects factor and Shape Position (first, second and third) as the within-subjects factor. It is important to note that this analysis excluded all shapes which were also targets, as these were analysed separately in our target vs non-target analysis. The ANOVA found no significant effects for N1 at any of the sites of interest.

Analysis of shape position: P1 time window (70-130 msec)

Given that, upon visual inspection, a P1 component was also evident in the data, we analysed this using the same time window as during exposure and two of the same sites of interest: PO7 and O1.

The Learning x Shape Position ANOVA showed a significant main effect of Shape on the P1 component mean amplitude at the PO7 site, $F(2, 42) = 18.262$, $p < .001$, $\eta_p^2 = 0.465$. Pairwise comparisons showed that the amplitude for shapes in position 2 was significantly higher than the amplitude for shapes in position 3 ($p < .001$), and shapes in position 3 had significantly reduced amplitude compared to shapes in position 1 ($p = .001$). There was no significant difference between shapes in position 1 and 2 (Figures 6.31 and 6.32). These results were consistent with those found at the O1 site.

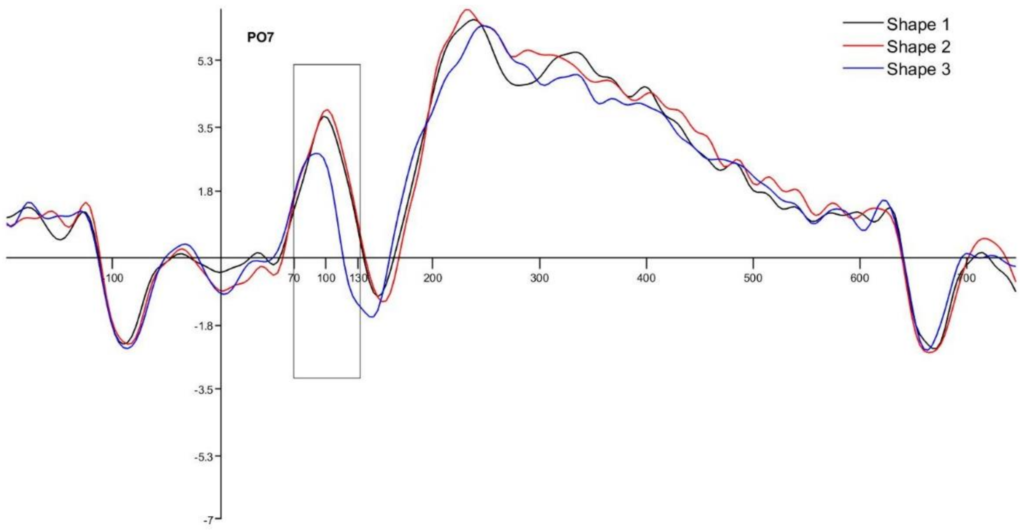

Figure 6.30: Grand average ERPs for P1 mean amplitude for shapes in position 1, 2 and 3 in the learners at PO7. Figure shows the reduced mean amplitude of shapes in position 3 compared to shapes in position 1 and 2. The rectangle contains the P1 time window (70-130 msec).

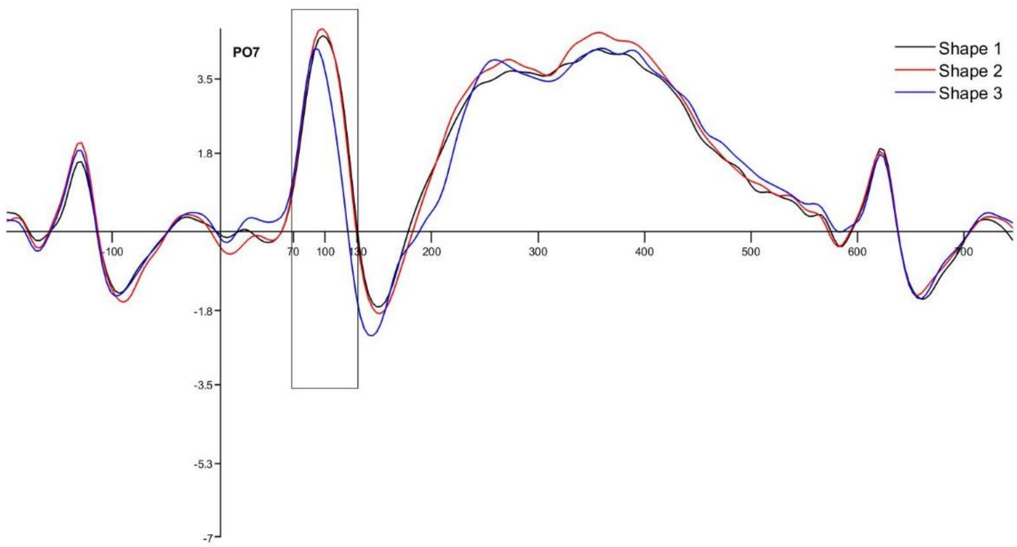

Figure 6.31: Grand average ERPs for P1 mean amplitude for shapes in position 1, 2 and 3 in the non-learners at PO7. Figure shows the reduced mean amplitude of shapes in position 3 compared to shapes in position 1 and 2. The rectangle contains the P1 time window (70-130 msec).

6.4 Discussion

The present study investigated the ERP correlates of implicit and explicit learning in a visual triplet learning paradigm. In the exposure phase we found that shapes in first position within a triplet had the highest amplitude in the N1 range. We also found an effect of shape position in the N400 component, this time resulting from higher amplitude for shapes in second than first and third position. The same shape position effect was also found in the P1 component, which also had higher amplitude for shapes in position 2 than 3 and 1. This was validated by results of the RSVP, which also found that, in the P1 component, shapes in position 2 had the highest amplitude. Effects of section emerged in the P1, N400 and P3b components, showing a larger mean amplitude in the first than second section of exposure.

With regards to our analysis of the P3b component, aimed at investigating differences in ERPs between implicit (guess attributions) and explicit (memory attributions) knowledge, we found no support in our data for a difference between the two. In fact, there were no differences in ERPs for guess and memory attributions, and no differences between learners and non-learners. The mean P3b amplitude consistently emerged as being, overall, larger for section 1 than section 2 of exposure.

In our 2AFC task, at O2 and PO8 sites we found significantly lower P1 amplitude for an old than a new triplet. Interestingly, we found no effect of learning, and no interaction between learning an old versus new triplets, indicating that the effect of old and new triplets appeared regardless of whether participants had been classified as learners or not. Our RSVP task successfully replicated the larger P300 effect to target than non-target shapes, thus providing a good quality control for all of our data.

Our first question of interest in this study was whether we could observe any ERP evidence of learning of the visual triplets. We chose our components of interest for this analysis on the basis of recent discoveries on ERP markers of learning in the visual triplet learning task. The larger amplitude which is usually observed for the N400 and N1 components for shapes in position 1 than position 2 and 3 within a triplet is referred to as the "triplet onset effect", and is taken as an index of triplet segmentation (Mandikal Vasuki et al., 2017). In the present experiment, we have obtained a significant main effect of shape position on mean amplitude of the N400 component which was driven by higher amplitude for shapes in position 2 than 1 and 3. Despite the similarity to the triplet onset effect, and the fact that it is based on shape position, our finding is in contrast to the triplet onset effect findings obtained by (Mandikal Vasuki et al., 2017), who found that shapes in position 1 had the highest amplitude. This prevents us from attributing these findings to triplet segmentation intended in this way. Interestingly, we found a similar effect in the P1 component which, consistent with our N400 results, also showed a main effect of shape position, consisting in highest amplitude for shapes in position 2 and reduced amplitude for shapes in position 3. This reduced shape 3 effect also emerged in the P1 component in our RSVP task, which further reinforced the relevance of shape position in this study.

Although an account of these findings based on the triplet onset effect as described by (Mandikal Vasuki et al., 2017) does not seem suited to these data, we suggest that the enhanced shape two amplitude in the N400, P1 and P3b components may be related to the predictability of the different shapes within a triplet. In fact, within the triplet learning paradigm, shapes in position 1 are entirely unpredictable based on the previous shape, whilst shapes in position 2 constitute the first predictable element within a triplet. The involvement of the N400, the P1 and the P300 components in mechanisms of predictability is well-documented within the existing literature. For example, (Batterink & Neville, 2013), in an investigation of ERP responses to syntactical violations in language, found that violations which were not explicitly detected in the behavioural test showed an early negativity between 100 and 400 msec which was maximal over left anterior regions. This supports the idea that the N400 we observed to shapes in position 2 within a triplet could be an index of predictability in our participants, despite the fact that a learning effect did not emerge through the behavioural test.

The idea that the P300 component is an index of predictability also finds support in the literature. (Jost, Conway, Purdy, & Hendricks, 2011) developed a visual statistical learning task, using coloured circles, in which statistical patterns determined the probability of a target stimulus occurring. The P300 component was found to be associated with participants' learning of the association between the predictor and the target. A larger P300 has also been related to temporal expectation in an Artificial Grammar Learning task (Selchenkova et al., 2014). With regards to the P1 component, this has also been found to be related to predictability, both temporal and spatial. In the example of an exogenous attention task, larger P1 responses were produced by visual targets that moved to predictable locations and at regular time intervals (Doherty, Rao, Mesulam, & Nobre, 2005).

In our analysis of the P1 component, we also observed an interaction between Learning and Shape Position, showing a larger difference between learners and non-learners for shapes in position 3 than shapes in position 1 and 2. Although the post-hoc tests for this effect did not reach significance, this seemed a promising finding, which, if replicated by future research, could shed light on mechanisms of predictability in the visual triplet learning task. In the present study, we can only speculate on a potential explanation. We suggest that it is possible that the lower amplitude we observed for shapes in position 3 compared to position 2 may reflect a decrease in surprise, given that this shape is now entirely predictable, and therefore does not produce a novelty effect compared to the previous shape. Based on this interpretation, it follows that, for learners, who are more subject to prediction mechanisms in this task, the decrease in P1 amplitude from shapes in position 2 to shapes in position 3 would be greater than for non-learners.

We tentatively suggest that our findings regarding the P1 amplitude could indicate the presence of implicit learning, intended as learning detected through the ERPs but not evident in the behavioural task, and that our participants had no awareness of. Our finding of reduced mean P1 amplitude to shapes in position 3 within a triplet, observed in the 2AFC analysis, which was found to be more pronounced in old than new triplets, appears to be in line with this suggestion. The fact that this effect was not different for learners and non-learners, as distinguished by the 2AFC task, might indicate that the learning effect in our participants was sub-threshold, and only evident in the ERP responses.

In our analysis of the N1 component we found a main effect of shape, consisting in higher amplitude for shapes in position 1 than position 2 and 3. This finding is consistent with previous findings of a triplet onset effect, which posits that higher N1 amplitude is observed to the least predictable element within a triplet, that is, the first element (Abla et al., 2008; Abla & Okanoya, 2009; Mandikal Vasuki et al., 2017). However, research on the triplet onset effect has shown that this is not present in participants who have not acquired knowledge of the triplets (Abla et al., 2008). This is in contrast to our findings that this effect was present for both learners and non-learners, and for both the first and second section of the exposure phase.

One possible explanation for this apparent contradiction could be that the N1 effect is, in actual fact, based on learning, but that the learning is too weak to be detected through behavioural performance, consistent with findings of non-conscious processing of stimuli which corresponds to certain neural events, in the absence of observable behavioural or conscious effects (Del Cul, Baillet, & Dehaene, 2007). This account implies that our classification of learners and non-learners on the basis of their performance in the 2AFC task is not a reliable reflection of whether learning was truly acquired, and it also highlights the benefits of the electrophysiological approach and the necessity for investigations of learning through ERPs. We therefore deemed this EEG study to have achieved one of its primary goals, in that it has detected the presence of learning-related effects in the absence of behavioural manifestations of learning.

Through our analysis of the 2AFC task, we aimed to discover whether there were any ERP markers of learning, even in the absence of a behavioural learning effect. For this reason, we compared ERPs stimulus locked to the first, second or third shape within an old (training) or a new (unseen) triplet. We analysed the P1 amplitude, and at the O2 and PO8 site we found significantly lower amplitude for old than new triplets. Despite our observed difference between old and new triplets, our results stand in contrast with previous research regarding old/ new effects in visual triplet learning (Ferdinand et al., 2010; Voss & Paller, 2008). In their analysis of the N1 component, Ferdinand et al., (2010) found that that old items were more negative than positive ones. In contrast, we did not find any significant differences between old and new items in our analysis of the N1 component. The authors did not carry out an analysis of the P1 component. However, there is a possibility that this component in our data might be an indication of learning in our participants. Interestingly, in this analysis, similar to our other analyses, we found no main effect of learning and no interaction between learning and old or new items, although, also bearing in mind the significant Learning x ShapePosition interaction that we found on P1 during the exposure phase, it is possible that learning-related effects may be found in future research with a larger sample size for learners. In the present 2AFC data, the difference found in the P1 component between old and new items was present regardless of our classification, based on behavioural performance, of participants as learners or non-learners. This is potentially a very interesting finding in terms of our aims in this study, as it might suggest that a learning effect was indeed present, but too weak or small to be observed through the 2AFC task. This learning effect, nevertheless, emerged in the ERPs.

Our analysis of the P3b component, aimed at investigating differences in ERPs between implicit (guess attributions) and explicit (memory attributions) knowledge, found no evidence of a difference between the two, and no difference in the P3b characteristics for learners and non-learners. In contrast, we found that, overall, the mean P3b amplitude was larger for section 1 than section 2 of exposure. This section effect is common to our other components of interest, the N400, P1 and P3b, and consistent across most of our other chosen electrode sites. It consists of a larger mean amplitude for our ERPs in the first than second section of the exposure phase. It is possible that this finding might reflect habituation by our participants in the second half of exposure, a well-known effect in the literature. Wintink, Segalowitz, & Cudmore, (1999) tested this with a memory n-back task, and found a decrease in frontal P300 amplitude after the first five blocks of the task, which they attributed to habituation to the task. This decreased P300 effect was mitigated by increasing the complexity of the task, which reinforced the habituation hypothesis.

Interestingly, in our analysis of the N400 component, we found an interaction between section and shape position showing that, whilst shapes in position 1 and 2 had a larger (more negative) mean amplitude in section 1 than 2 of exposure, which would be consistent with a habituation account of this effect, the opposite was true for shapes in position 3, which showed a larger mean amplitude in section 2 instead. We suggest that, in a similar way to the P1, this might be linked to the higher predictability of shapes in position 3 within a triplet. Since learning should have taken place by the second section of exposure, the larger amplitude in the section for shape 3 could be linked to a fulfillment of expectation which we do not observe in section 1, given that less learning would have taken place then. As this interpretation is based on an isolated interaction effect in this experiment, however, we recommend future replications of this effect before drawing any firm conclusions.

For what concerns our RSVP task, the present study has replicated the well-known effect of a larger P300 for target than non-target stimuli (Baldwin & Kutas, 1997) (Trippe et al., 2007). In this sense, our RSVP results also act as a form of quality control for our data, and increase confidence in the results we have obtained. The results of our analysis for this task are also in line with our findings of different ERP characteristics for shapes in position 1, 2 and 3 within triplets, replicating our P1 and N400 effects of larger amplitude for shapes in position 2. Following on from our account of this effect as a marker of prediction within our triplet learning task, this could be an important finding for the RSVP task in the context of our research. It would, in fact, show that mechanisms of predictability operate in this task, despite the fact that we have so far, in the present chapter and in Chapter 4 of this thesis, been unable to detect any triplet knowledge through behavioural analysis of response times.

Of the visual triplet learning experiments carried out in this PhD, the present study was the one with the poorest behavioural performance. In fact, average 2AFC performance for the whole sample of participants did not reach above-chance level. The overall poor performance has presented a methodological problem for the present study which was twofold. Firstly, our sample of learners was considerably smaller than our sample of non-learners, which may have affected the outcome of our statistical analyses. Secondly, the majority of participants utilised either guess attributions only, which greatly reduced the sample size available for within-subjects comparisons, or a larger number of guess than memory attributions. The imbalance of guess and memory attributions used by participants also meant that the grand-averaged waveforms relating to guess attributions were calculated on the basis of a much smaller number of trials than the waveforms relating to memory attributions.

At this point, it is important to acknowledge that the lack of significant learning effects in our behavioural data pose a challenge for the interpretation of ERP findings. In fact, at the core of the ERP technique is the matching between neural responses and behavioural events (Luck, 2005). Given the absence of behavioural effects in our data, the conclusions that we have been able to draw regarding the presence of implicit or explicit knowledge reflected by our ERPs are to be interpreted with caution, and remain at a speculative level until they are confirmed by further research. Nevertheless, this work sets the basis for future studies using ERPs in the context of visual triplet learning by drawing attention to the methodological challenges that future research will have to face. Notably, it will be necessary to achieve an above-chance level of behavioural performance and a sufficient use of both Guess and Memory attributions to allow for comparison of ERP responses between the two.

One possible cause of the lower behavioural performance that we have observed could be the use of a cover task during exposure. In our experiment carried out in Chapter 4 on a sample of children, we did not find any detrimental effects of a secondary task on performance in this age group and, although we found some suggestions in the same chapter that a secondary task may be detrimental to performance in adults, the results of that experiment were also confounded by the greater amount of exposure that was administered to those participants.

Another factor which could have influenced behavioural performance in the present experiment is the order of tasks. In fact, the RSVP task in this experiment was presented immediately after the exposure phase, in the same way as (Bertels et al., 2015b). There is a possibility that the RSVP task may have negatively influenced participants' performance in the forced-choice task. It may be hypothesised, for example, that focusing on this task may have induced fatigue in participants. The possibility that engaging in the RSVP task may have induced forgetting seems less plausible, given that the RSVP trials consisted of the same triplets that were seen during exposure and should have, therefore, reinforced learning.

Another factor to consider in the behavioural performance in the present experiment was the speed of visual stimulus presentation. In fact, this experiment used epochs of 750 msec (500 msec for stimulus presentation and 250 msec for the inter-stimulus interval). This was the necessary epoch length for the recording of ERPs. In contrast, the slowest stimulus presentation used in Chapter 5 of this thesis was 400 msec for the shape presentation and 200 msec for the inter-stimulus interval. Based on the present findings, the effects of speed on behavioural performance in ERP studies of visual triplet learning is something that future studies should carefully consider.

Overall, the present experiment has made a significant contribution to the knowledge on implicit and explicit Statistical Learning that we have built so far in this thesis. Our results are in agreement with the behavioural findings that we have obtained so far, in that we were unable to identify clear ERP markers of implicit and explicit knowledge. This is in line with our behavioural evidence gathered so far in our work, that there is likely to be no implicit knowledge in this form of learning. We have also made an important contribution in terms of understanding the behavioural measures of conscious knowledge in the Statistical Learning paradigm. In the present experiment we have, in fact, found some evidence that there are effects of learning or prediction in this task which are too weak or low- level to be detected through behavioural measures. Given these findings, we suggest that, in order to move forward in the understanding of knowledge in Statistical Learning, research should rely on a combination of behavioural and electrophysiological measures.

Chapter 7 Discussion and conclusion

7.1 A summary of the key findings of this thesis

This thesis investigated implicit and explicit knowledge in auditory and visual statistical learning. Chapter 2 established that the Process Dissociation Procedure (PDP) and the guessing and zero correlation criteria can be used to assess the status of knowledge of auditory stimuli generated through a transition matrix. We found successful learning in both adults and children, and that both age groups were aware of the knowledge that they had acquired and could control its use. We also concluded that visual stimuli generated through a transition matrix appear to be too complex for learning to occur, and, therefore, that the transition matrix paradigm cannot be used for the study of visual statistical learning.

In Chapter 3 we successfully investigated the type of knowledge acquired in a triplet learning paradigm in both the auditory and visual modality through the same use of our combined methods: the PDP and the guessing and zero correlation criteria. Both these measures of conscious knowledge indicated that participants were fully aware of the visual and auditory triplets learned. We found that a bias towards specific triplets, which interferes with learning, is present in both the visual and auditory triplet learning task. Due to this bias being stronger in auditory triplet learning, we decided to abandon this paradigm and retain the transition matrix paradigm for the study of the auditory modality.

Chapter 4 was aimed at validating and consolidating the findings of explicit knowledge obtained this far by using a combination of direct (forced-choice tasks) and indirect (Rapid Serial Visual Presentation Task) measures of conscious knowledge in a visual triplet learning paradigm, and additionally compared adults and children. Our indirect measure of knowledge did not detect any more knowledge than the forced-choice tasks. This lack of a dissociation between the two types of measures reinforced our confidence in the methods for measuring conscious knowledge used this far, which did not miss any unconscious knowledge that may have been present. In line with our previous results, the knowledge acquired was found to be prevalently explicit in both adults and children. Through the use of a generation task, we found that the successful performance in the forced-choice tasks, and our participants' awareness of the acquired knowledge, did not coincide with the ability to explicitly recollect the training material.

Given the scarce evidence found so far for the presence of implicit knowledge in statistical learning, in Chapter 5 we investigated the hypothesis that implicit and explicit knowledge are dependent on the speed of stimulus presentation. We investigated a fast, baseline and slow speed of presentation in both the visual and auditory modalities, aiming to assess whether a faster presentation speed leads to more implicit knowledge. We found that, although statistical learning can take place at all three presentation speeds, participants' knowledge is weaker at a faster speed. Knowledge appeared more implicit at faster stimulus presentation speeds and more explicit at slower speeds. Perceptual abilities within musical sophistication were significantly correlated with explicit, but not implicit, knowledge in auditory statistical learning.

In Chapter 6 we aimed to investigate the electrophysiological correlates of implicit and explicit knowledge in visual statistical learning. Specifically, whether guess (implicit) and memory (explicit) responses generated different ERPs, and therefore whether any implicit knowledge had been missed so far due to the poor sensitivity of the behavioural measures. There were no differences in in ERPs between implicitly and explicitly learned triplets in either learners or non-learners within our sample. However, in our data we found suggestions that a learning effect may be present and detectable through the ERPs in the absence of above-chance behavioural performance. This is potentially a highly interesting finding which will have to be validated through further electrophysiological investigations.

7.2 Theoretical and methodological implications of our work

Our work has both theoretical and methodological implications, which are intertwined to form a complex picture. Looking at our contribution to theory in the field, this thesis has found that participants mainly develop awareness of what they know in statistical learning, and are able to control the use of this knowledge. Through our combination of generation and recognition tasks, we have shown that this awareness, however, does not correspond to explicit recall, intended as the ability to reproduce the learned material. In fact, our research has shown that, whilst participants lack the ability to recollect and reproduce their knowledge of training fragments, they can nevertheless inhibit the use of this knowledge, as assessed through the PDP, and are able to track the correctness of their responses, as assessed through the guessing and zero correlation criteria. Within the context of our 2-alternative forced-choice task, both these abilities stem from participants' recognition memory of the training fragments, rather than recollection. For this reason, on the basis of the experimental tasks used in this work for the measurement of conscious knowledge, we refer to the explicit knowledge acquired by our participants, and by participants in previous work, as "awareness of recognition". In this sense, our original contribution with this work also extends to clarifying the meaning of implicit and explicit knowledge in studies in this area which use the same experimental approach as our research.

With regards to our methodological contribution, this thesis has developed a methodology for the measurement of implicit and explicit knowledge in statistical learning based on the use of combined measures. To the best of our knowledge, the use of the PDP and guessing and zero correlation criteria with the auditory transition matrix and visual triplet learning paradigms has not been implemented in previous research. Our work indicates that this combination of techniques is, indeed, a suitable method for the measurement of the status of knowledge in statistical learning. Furthermore, the occasional lack of agreement between the two measures has provided us with useful information regarding the reliability of the guessing and zero correlation criteria.

Our findings have also drawn attention to aspects of our chosen statistical learning paradigms that future research should take into greater consideration, as they could confound genuine statistical learning effects, therefore representing an obstacle to investigations and development of knowledge in this area. These include the existence of participant biases towards certain stimulus fragments in both visual triplet learning and auditory transition matrix stimuli, and potential methodological shortfalls of the RSVP task.

In terms of the conclusions we can draw regarding our main question of implicit and explicit knowledge, throughout our work, we have found that knowledge in visual and auditory statistical learning is predominantly explicit. Our data, however, suggest that implicit knowledge might be present at faster speed of stimulus presentations in both the auditory and visual modalities (Chapter 5). The fast condition of speed in this experiment is also the condition in which we have observed the most agreement between our measures of conscious knowledge. Despite this convergence of results, we caution against drawing firm conclusions in favour of the presence of implicit knowledge and believe that it is also important to consider alternative explanations of our findings throughout our work. This is motivated by the fact that we have occasionally observed contradictions between our measures of conscious knowledge. Appendix H provides a summary of the results obtained in our experimental chapters, and illustrates these contradictions.

Based on an observation of our pattern of results, it may be possible that the zero correlation criterion tends to indicate implicit knowledge when the learning effect is small, as a product of participants' generally low confidence in their responses. This hypothesis is supported by the results of our auditory experiment in Chapter 3. The learning effect in this experiment was smaller for participants trained on L1 than participants trained on L2 and the zero correlation criterion indicated implicit knowledge, that is, no difference in confidence between correct and incorrect responses for L1 participants but not L2 participants under both inclusion and exclusion conditions. A similar pattern of results is observable in Chapter 4, in which we tested two versions of the visual triplet learning experiment, Version 1, with a distractor task and a smaller amount of training, in which the learning effect was relatively small, and Version 2, with no distractor task and a greater amount of training in which we obtained a greater learning effect. The zero correlation criterion showed implicit knowledge in the experiment version with the smaller learning effect but explicit knowledge in the experiment version with the greater learning effect.

Interestingly, in Chapter 5 we also observed a contradiction in the auditory fast stimulus presentation condition between the zero correlation criterion and the PDP and guessing criterion. In fact, whilst the PDP and guessing criterion seemed to agree that knowledge was implicit, the zero correlation criterion indicated that it was explicit. The fact that confidence when correct was higher than confidence when wrong whilst participants, according to the guessing criterion, were not able to track their knowledge, is a contradictory finding. We propose that it could be explained by a discrepancy in sensitivity between the guessing and zero correlation criteria. In fact, if viewing guessing as a categorised form of confidence, it can be seen that, if participants below a certain confidence level labelled their responses as guesses, this may reduce the guessing criterion to an underpowered measure compared to the zero correlation criterion, which is based on a higher-resolution confidence scale. Within this context, it can also be seen how contradictions between the guessing and zero correlation criteria might have arisen in the fast stimulus presentation condition due to the learning effect being smaller than in other conditions. In any case, the lack of consistency between these two measures casts doubts over the reliability of our results regarding the presence of implicit knowledge. Similarly, with regards to the zero correlation criterion in Chapter 5, this indicated implicit knowledge, or non-interpretable results, in conditions in which the learning effect was smaller.

In Chapter 5 we also found a contradiction in the baseline and slow stimulus presentation conditions, in which the guessing criterion had indicated either implicit or non-interpretable knowledge, whilst the PDP had indicated explicit knowledge. It is possible that, when the learning effect is small, and trials in which participants are guessing, using their intuition or their memory are separated, sufficient statistical power for a reliable analysis cannot be reached. This leads to a broader consideration regarding guessing and zero correlation criteria. These are measures which rely on the interpretation of a null result, that is, the lack of a difference in confidence ratings between correct and incorrect responses, in the case of the zero correlation criterion, or the lack of above-chance performance, in the case of the guessing criterion, for the detection of implicit knowledge. It follows that a sufficiently high statistical power is necessary for these measures to yield a reliable result, otherwise, the lack of a significant effect might be interpreted as implicit knowledge due to lack of power, rather than to the genuine presence of implicit knowledge.

The performance of the guessing and zero correlation criteria in the presence of a low learning effect is an important issue. In support of our findings in this thesis, it has been noted by recent literature in the area (Siegelman, Bogaerts, Christiansen, & Frost, 2017) that there is a tendency for the majority of participants to perform around chance level in the classic visual triplet learning task. This casts doubt over whether the guessing and zero correlation criteria are appropriate measures of conscious knowledge for this paradigm, given that they are highly likely to be used in the presence of low participant confidence. Aiming to make methodological improvements to our paradigms, our future investigations should make use of d' measures of meta-cognition, which have been suggested to be more suitable in handling the problem of participant bias in Sequential Regularities Learning paradigms (Barrett, Dienes, & Seth, 2013; Berry, Shanks, Speekenbrink, & Henson, 2012).

Our hypothesis put forward here that contradictions between measures of conscious knowledge arise in the presence of a small learning effect is reinforced by our analysis of learners only in Chapter 5 of this thesis, which showed agreement between our different measures of conscious knowledge, all indicating that knowledge was explicit in this group. This is further supported by the fact that we have observed the most explicit knowledge in our auditory experiments, which were also the ones in which the learning effect tended to be greater. Based on this, we could make a tentative suggestion that, in the presence of a sufficiently large learning effect, knowledge would result to be entirely explicit in these behavioural tasks.

It is also important to highlight a caveat regarding the explicitness of knowledge in this work, however. In this thesis we adopted an awareness-based definition of implicit knowledge, conceptualising it as knowledge that participants are not aware of. When working under this definition, in order to measure implicit learning, it is necessary that a certain experimental setup is in place, as the implicitness of learning is ensured through the implicitness of experiment instructions (Rebuschat, 2013). We are aware, however, that, given that almost all of our sample consisted of psychology students, the implicitness of instructions may not have been a strong enough measure to ensure implicitness of learning, due to the participants' knowledge about psychological experiments which may have influenced their expectations about the aims of our investigation. Therefore, the nature of our sample might have contributed to biasing our results towards explicit knowledge.

Against our argument that knowledge in Statistical Learning is mostly explicit, it could be claimed that in our experiments implicit knowledge was present that we have not managed to detect. In response to arguments of this kind, we suggest that, for what concerns our behavioural investigations, we endeavoured to ensure that we were testing all relevant knowledge. For example, the fact that there was no dissociation between direct and indirect measures of knowledge in Chapter 4 reinforces our confidence that our behavioural measures did not miss any implicit knowledge which may have been present. Furthermore, with regards to those experiments in which performance was at chance, we suggest that implicit knowledge of a sufficiently strong level should still have allowed successful performance in the 2AFC task. Therefore, we suggest that, if any implicit knowledge is present in Statistical Learning, as measured through our Transition Matrix and Visual Triplet Learning paradigms, this cannot be detected using the available behavioural measures, and that these measures will tend to show more explicit knowledge the greater the learning effect.

There is, however, the possibility that some implicit knowledge was indeed present, but too weak or low-level to be detectable through behavioural measures. This is a possibility that we investigated in Chapter 6, through the use of ERPs. The EEG approach is useful for the detection of any learning effects which are not manifested in behavioural tasks (Bogaerts, Siegelman, & Frost, 2016). Our work in Chapter 6 seems to provide some preliminary suggestion that some implicit knowledge might have been present, although this will need to be validated by further research. We suggest that any future investigations in this area should use a combination of behavioural and electrophysiological approaches.

In this thesis we adapted the Process Dissociation Procedure (PDP) for use within a forced-choice task in statistical learning. To the best of our knowledge, this is the first application of the PDP within the visual triplet learning and auditory transition matrix paradigms. In statistical learning research, the PDP had mainly been applied in the context of motor learning, with the SRT task (Bischoff-Grethe et al., 2004; Norman & Price, 2010; Fu et al., 2008a; Fu et al., 2013), and within auditory triplet learning using artificial speech by Franco et al., (2011a), although the application of the PDP by these authors consisted in a yes/ no decision on one test item whilst we used a forced-choice task between two test items. As ours is a new application of the PDP, it is necessary to evaluate the extent to which the implementation of this technique furthers our understanding of implicit and explicit knowledge in statistical learning, and the importance of our methodological contribution to the field.

As illustrated in Appendix H, in Chapter 5 of this thesis, in the visual baseline condition and auditory slow condition, we observed a contradiction between the PDP and the guessing criterion. The guessing criterion indicated implicit knowledge which, as we argued above, could also have been a result of poor knowledge overall and low confidence whilst, at the same time, the PDP indicated that explicit knowledge was present. In this respect, it could be argued that the PDP is more sensitive to conscious knowledge than the guessing and zero correlation criteria because, whilst these criteria rely on a combination of confidence and correctness, the PDP does not take confidence into account but, instead, merely relies on a comparison of inclusion and exclusion performance. Therefore, we suggest that this technique may be more suitable in the presence of low participant confidence, a suggestion related to our proposal made above that the knowledge that can be measured through behavioural methods in our tasks is entirely explicit. From a methodological point of view, the combination of measures in our experiments has revealed information about the different sensitivity of the PDP and guessing/ zero correlation criterion and their suitability for measuring conscious knowledge in statistical learning.

Some authors have defined the forced-choice task as intrinsically explicit (Turk-Browne et al., 2005; Kim et al., 2009), and its use in the context of research attempting to measure implicit knowledge has recently been criticised on the grounds that, by making direct reference to the material to be tested, the forced-choice task biases participants towards explicit knowledge (Siegelman, Bogaerts, Christiansen, & Frost, 2017). This criticism also applies to the present work, given that our performance measures are based on completion of a forced-choice task under inclusion and exclusion conditions. As a solution to this issue, Isbilen, Mccauley, & Christiansen (2017) proposed a variation of the 2AFC task called Statistically Induced Chunking Recall (SICR) task. By not using explicit instructions, this task is thought to be able to detect knowledge which is below the conscious threshold. The task, administered after the exposure phase with an auditorily-presented artificial language, requires participants to repeat out loud, immediately after auditory presentation, fragments of the artificial language stimuli belonging to the exposure phase or previously unheard, randomly concatenated elements which did not form an exposure fragment. Performance is measured in terms of the number of correct syllables repeated.

We see a flaw in the rationale for the SICR test as testing implicit knowledge. In fact, the authors' claim is based solely on the fact that the test does not make direct reference to the specific discriminations to be made by the participant. However, as the task is based on explicit recall of chunks, it could still be claimed to test explicit knowledge, similarly to the tasks that it proposes to improve on. In defence of our use of the PDP for the measurement of participants' knowledge, we argue that, given the slow progress in resolving the methodological challenges present in this area of research, no other options were available for the development of PDP in the context of a 2AFC task.

Developing a behavioural task which would have enough sensitivity to unconscious knowledge has been a challenge which other researchers had also previously attempted to address. An example of this is the RSVP task which, due to its indirect nature, was claimed to be more sensitive to unconscious knowledge than direct, forced-choice measures (Bertels et al., 2015a, 2012b). The results of our work have highlighted potential methodological concerns around this task. Namely, the fact that participants might forget which shape target they are required to respond to during each test stream, and the fact that different data analysis strategies for the response times, in terms of the time window that is chosen for a correct response, might lead to different results. Furthermore, in our experiments, the RSVP did not show sensitivity to participants' knowledge of the triplet structure and, when an effect was observed, the size of this was small. Based on the challenges encountered by research on this topic, which the findings of the present thesis reinforce, we suggest that agreement regarding a suitable behavioural measure of implicit knowledge in Statistical Learning has not yet been reached to date. Given that behavioural studies in this area have been carried out for several decades, the question emerges whether research should continue to pursue the question of implicit and explicit knowledge in Statistical Learning through behavioural approaches, or whether a change in methods and approaches is necessary in order to progress in this area.

Finally, in terms of the implications of our findings, and how they fit within the context of existing research, it is also important to draw attention to the question of individual differences in statistical learning performance, a result which emerged throughout our work in this Thesis. Siegelman, Bogaerts and Frost (2017), based on a review of existing studies which make use of classic statistical learning tasks, observe that the majority of participants perform around chance, with only a few individuals excelling at the task. The authors argue that, in light of this high variability between individuals, performance measures which are based on central tendency are not a true indication of performance. This is something which consistently emerged in our data, and is visible through our representations of performance in the dot plots in Chapter 4 and Chapter 5. Through these, we aimed to provide a more informative representation of performance within our samples.

In our work in Chapter 5 we attempted to shed light on the sources of these individual differences by investigating the correlation between performance, digit span, reading abilities, and musical sophistication. However, we are aware that discrepancies between the ways in which the various cognitive abilities are measured in different studies make comparison challenging, and we argue that no clear picture of the source of these large individual differences exists yet. We suggest that future studies of Statistical Learning should routinely quantify and report individual differences between participants, rather than focus solely on measures of central tendency. We believe that understanding this variability in performance is a key step in understanding the statistical learning ability itself. Once the source of these is better understood, research will be able to expand by focusing more fruitfully on how statistical learning performance can be used to predict other cognitive abilities.

7.3 The measurement of implicit and explicit knowledge: recommendations for researchers

Based on the findings of this Thesis, in this section we make a number of recommendations for researchers wishing to pursue the question of implicit and explicit knowledge in statistical learning or, indeed, for those wishing to assess the status of knowledge of the learned material within other, related, fields. Our confidence in these recommendations stems from our work in Chapter 4, which showed that our measures are effective in detecting all the relevant knowledge available for measurement, as far as behavioural measures alone allow.

In this thesis we have developed a method for the measurement of implicit and explicit knowledge in Statistical Learning that is based on the combined use of the PDP and the guessing and zero correlation criteria. We have shown that these three measures have different degrees of sensitivity to conscious knowledge, as shown by their occasional lack of agreement, and we therefore recommend their combined use. In fact, our measures can successfully act as mutual control for each other, whilst compensating for each other's lack of sensitivity for specific types of information. It has transpired that the PDP, as a solely objective measure of performance which does not take confidence into account, may be more sensitive to participants' explicit knowledge. On the other hand, confidence ratings as measured by the zero correlation criterion provide valuable insight into participants' subjective feeling of knowing, or meta-knowledge (Fleming & Lau, 2014).

In our work we observed that the guessing criterion, seen as a lower-resolution form of a confidence scale, may be less sensitive to explicit knowledge than the zero correlation criterion. Despite this, we recommend its use in combination with the above-mentioned measures, because of the qualitatively different type of information that the "guess", "memory" and "intuition" knowledge attributions are able to provide. These can, in fact, point to the type of information about the to-be-learned structure that was acquired by participants. Of note, within the context of AGL paradigms, "memory" attributions have been classed as "structural knowledge" attributions (Dienes, Zoltán, & Scott, 2005a), as they are seen as indicating awareness of the structure of the stimuli by participants, whilst "intuition" attributions have been classed as "judgement knowledge" attributions, as they indicate awareness that a test item is correct, in the absence of knowledge as to why it is correct (Dienes, Zoltán, & Scott, 2005a).

It has also emerged from our work in Chapter 4 that awareness of recognition of the training items by participants does not coincide with the ability to reproduce the learned stimuli in a generation task. For this reason, we recommend that researchers begin making routine use of the generation task in combination with the PDP, guessing, and zero correlation criteria. This will be useful in further assessing the extent of participants' awareness, and whether this coincides with an ability for explicit recollection. Only very few of our participants were able to reproduce at least one of the visual triplets learned, showing that their explicit recognition coincided with an ability for recollection, whilst the large majority were not able to reproduce any of the triplets. We see the generation task as a valuable tool in the identification of these individual differences between participants in the quality of the knowledge acquired, and an important starting point in the investigation of why these differences exist.

7.4 The challenges for Statistical Learning tasks discussed in the context of current literature

Recent literature in the field has raised concerns about the reliability of traditional statistical learning tasks in relation to the ability of existing measures to discern between different degrees of learning in participants (Siegelman et al., 2017). One of these concerns revolves around the number of test trials in a classical statistical learning task, typically based on four familiarisation triplets, involving only four unique decisions in the test phase. Siegelman et al., (2017) propose that a much larger number of trials would be required in order to introduce larger variance in the sample and reduce measurement error.

Although we concur with the authors that a test phase involving a greater number of trials would improve discernibility between participants, we are also aware that this would present practical difficulties in terms of implementation. Our test phases in the present work lasted up to a maximum of forty-five minutes. Based on the informal feedback that we consistently obtained from our participants about the length of our testing session, we believe that a longer test phase would be too tiring for participants. As well as performance being affected by fatigue, with a longer test phase there is also the possibility that participants might forget the exposure stream, and that unseen fragments from the test phase might be confused with fragments seen during exposure. This is something that our participants have occasionally commented on, by pointing out that, by the end of a test phase, they "did not know which fragments were familiar through exposure and which were familiar through the test phase anymore". This is particularly true of our longer test phases which require administration of the forced-choice test twice, once under inclusion and once under exclusion as part of the PDP. Furthermore, as Siegelman et al., (2017) pointed out, if the number of repetitions of each triplet in the test phase is increased, there is a risk that participants might acquire knowledge during the test phase. Our comparisons of performance in the first and second half of the test phase in our work have shown that no learning has taken place during the test. This, however, would become a risk if we increased the number of repetitions of each triplet.

Siegelman et al., (2017) also raised a further, related issue around reliability in typical statistical learning tasks. Test items are usually of the same type and level of difficulty, in fact, visual triplet learning tasks assess participants' ability to discriminate between two types of triplets: those in which the transition probabilities between shapes equal one and those in which they equal zero (foil triplets). As a consequence, the forced-choice test only assesses a limited part of the statistical learning ability that it aims to measure, given that visual statistical learning requires different types of computations, such as discriminations between sequences of different length and complexity, tested not only through recognition, but also through production. Siegelman et al., (2017) argue that the restricted range of test items is responsible for the poor efficacy of the test in discriminating between individuals. This is an issue that the transition matrix paradigm addresses, with its ability to generate stimuli based on a variety of different-order statistics, and to control which order of statistics are being used (Durrant et al., 2011b; Durrant et al., 2013a; Durrant et al., 2016). However, based on the results of our experiments in Chapter 2, we suggest that this paradigm would only be suitable for use in the auditory modality, and therefore would not resolve the problem surrounding existing measures of visual statistical learning.

The use of test items of varying levels of difficulty is also something that we could have investigated in this work through the transition matrix paradigm. This is highly flexible and allows to control not only the order of transition probabilities, but the adjacency of the statistical dependencies and the types of sequences: probabilistic or deterministic. Previous transition matrix work in the auditory modality has indeed used auditory test sequences of different levels of difficulty, and shown an effect of difficulty across three levels which reflected in behavioural performance (Durrant et al., 2011b). It may be beneficial for future research to combine this with variations in length of test sequences within the same test phase instead of separate experiments, as in Chapter 2 of this thesis, as well as including both a recognition and a production test. For our future research, manipulating the difficulty of test items might help to shed light on the question of implicit and explicit knowledge. It is, in fact, possible that more implicit knowledge may result from learning of more complex items.

Based on the discrepancy in performance between the visual and auditory modalities observed in our work, we hypothesise that a test phase containing variations in levels of difficulty of the test items would be more successful in the auditory than the visual modality, given that the auditory modality is characterised by better participant performance. Given that the majority of participants in our visual triplet learning experiments performed around chance level, which may indicate that participants found the task difficult, we expect that a test phase containing items of varying levels of difficulty would be challenging to implement in future research. Our early transition matrix experiments in the visual modality are also in line with this suggestion, indicating that visual sequences generated through transition matrix are too challenging to retain in memory. Those experiments attempted a wide variety of paradigms and modes of presentation for the visual modality but failed to obtain above-chance performance. One further caveat to consider, relating to both the auditory and visual modality, is that including different levels of difficulty would also entail lengthening the duration of the task, therefore incurring in the problems mentioned above relating to task length. This is particularly true when considering implementation of a longer task alongside the PDP, which requires the administration of two different sets of instructions, therefore already doubling task duration.

In order to address these issues around the power of discrimination between individual participants, Siegelman, Bogaerts, & Frost, (2017) implemented a variation on the standard visual TL task which contains an increased number of test items, therefore reducing noise and leading to a larger number of above-chance performers, and test items of different levels of difficulty, which require different types of computations. The authors suggest that this version of the task has improved sensitivity to different levels of participant knowledge. We argue that, although a larger number of test items with greater variability would have higher resolution in detecting participants' knowledge, the increased length and difficulty of such a task would pose challenges to its implementation, particularly in the visual modality. The range of methodological difficulties discussed seems to suggest that the development of suitable methodologies to investigate SL is still in its infancy and will require further attention from future research.

7.5 The use of different types of statistics for successful learning

Recent research is coming to better understand the complexity of Statistical Learning, seen as a fundamental cognitive function, which encompasses different kinds of abilities: knowledge of transition probabilities, chunking, sensitivity to repetition, sensitivity to global and local statistics, and cues for segmentation (Siegelman et al., 2017). The extraction and integration framework points to the importance of both conditional statistics, such as transition probabilities, and distributional statistics, such as the frequency and variability of individual items, in the to-be-learned stimuli (Thiessen, Kronstein, & Hufnagle, 2013). It is important to note, however, that not all types of tasks are sensitive to all types of statistics (Siegelman et al., 2017).

As in this work we were interested in learning based on the processing of Transition Probabilities (TPs), we have adopted traditional statistical learning tasks where TPs generated the statistical structure of the stimuli. In our auditory transition matrix experiment in Chapter 2 we observed that a large amount of context (eight-element test sequences) was needed for participants to be able to relate the test items to the exposure stream. Based on this observation, we hypothesise that participants' decisions on the test items might have been influenced by general properties of the test streams such as same-element repetitions. Therefore, although the statistical regularities in the transition matrix paradigm are, indeed, determined by transition probabilities, and intended to measure sensitivity to conditional statistics, we suggest that participants may have heavily relied on frequency statistics for successful performance by, for example, identifying salient same-element repetitions, which they may have grouped as "chunks" in the exposure stream, and looking for them in the test sequences. We could not verify this suggestion empirically, as our experiments in this work did not have a way to test which types of statistics were being used by participants.

Future research should implement measures to attempt to tease apart participants' use of the different types of statistics required when making discriminations between test items. In fact, to date, there does not seem to be a measure of Statistical Learning which captures the complexity of the various computations which participants engage in. Classical forced-choice tests, like the ones we have used in our work, require participants to recognise fragments, or chunks, which belong to the exposure stream. In the selection process, participants are able to compare the test fragments to what they remember from the exposure stream, but can also compare one test fragment to the other to aid their decision. Based on our findings in this work, we suggest that there are factors other than sensitivity to conditional statistics which are heavily influential on participants' decisions. One example of this is our hypothesised use of frequency statistics in our auditory transition matrix experiment in Chapter 2 and the preference for certain shapes or arrangements of shapes discussed in Chapters 4 and 5 in the context of our visual triplet learning task.

7.6 Perceptual fluency as an account for test item preferences

We propose that the participants' biases towards specific shapes that we have observed in this work deserve further discussion. In explaining potential reasons underpinning these biases in Chapters 4 and 5, we discussed the hypothesis that participants might have engaged in verbal labelling of the individual shapes, and preferred the shapes which could be labelled more easily. Another potential explanation for this finding, which has been prominent in Sequential Regularities Learning research, revolves around perceptual fluency.

Perceptual fluency, defined as the ability to rapidly encode and remember items, has recently been seen as a potential explanatory factor for performance in statistical learning tasks, despite being an ability unrelated to statistical learning skills (Perfors & Kidd, 2018). The fluency theory is based on the mere-exposure effect, postulating that, when a stimulus is presented repeatedly, this increases perceptual fluency for that stimulus. This, in turn, is thought to increase liking for that stimulus, due to participants misattributing the feeling of fluency to liking (Newell & Shanks, 2007). This positive affect towards the stimulus induces in participants a sense of intuition for the correct response (Topolinski & Strack, 2009). The fluency hypothesis is prevalent in AGL paradigms, in which it is thought to play a role in grammaticality judgements (Chang & Knowlton, 2004; Kinder, Shanks, Cock, & Tunney, 2003).

The perceptual fluency theory applied to Sequential Regularities Learning research can be linked to the results of our triplet preference analysis. Within the perceptual fluency theory, perceptual ease of processing induces positive affect for a stimulus and an intuition that the stimulus constitutes a correct response. In the case of our visual triplet learning experiment, some shapes may have been perceptually easier to process due to properties such as, for example, simpler lines, or occupying a smaller area. This ease of visual processing might have increased perceptual fluency for them, and, in turn, generated a sense of liking for those shapes, leading participants to choose triplets which contained them. We see this triplet preference effect as a methodological concern around the visual triplet learning paradigm, as it could potentially confound genuine learning effects. In fact, perceptual fluency and, subsequently, liking for particular shapes may lead participants to endorse a triplet as belonging to the training stream regardless of its correctness. We suggest that this concern applies in a similar way to the auditory domain, as we have shown in Chapter 2, in which it emerged that pre-existing preferences for certain tone triplets, present in participants through tonal enculturation, could contribute to certain triplets being preferred, regardless of learning.

Although, to the best of our knowledge, we are the first to analyse triplet preference effects in the visual triplet learning paradigm, we did not devise any experiments which were specifically devoted to investigating the origins of these preferences, as this was outside the scope of our research. Therefore, the suggestions we have made regarding this effect are, at present, only on a speculative level. However, whether preference in our participants was due to memorability or ease of processing of certain shapes, this finding is an important contribution to the field, as it points to a methodological concern of the visual triplet learning task. In our view, this has not been investigated enough in research to date, with only very few authors pointing to the fact that Statistical Learning is dependent on the types of stimuli used (Noam Siegelman & Frost, 2015; Knast, Durrant, Miranda, & Denham, 2008 – unpublished work). Future investigations should not only focus on the origins of shape preference effects, but also incorporate triplet preference analyses as standard in these experiments.

Perceptual fluency is a strategy for forced-choice task performance which is not based on active recollection and, for this reason, it is considered to be implicit in nature (Kinder and Shanks, 2003). In line with this proposal, to the extent that our participants' performance was guided by perceptual fluency, we could hypothesise that they were using an implicit process. Relating the existing theory around fluency to the knowledge attributions that we have used in our work, we could further speculate that fluency in our participants may have been captured by "intuition" attributions, and that these attributions are implicit in nature. The sensation of familiarity induced by fluency, which our intuition attributions might have captured, could also be explained by what is referred to in the literature as "fringe of consciousness" (Mangan, 2001).

Although only on a speculative level for now, suggestions could be made regarding the role of fluency-based strategies on implicit knowledge. For example, it could be that, if perceptual fluency is an important process in the visual triplet learning paradigm, and if it is an implicit process in nature, then decisions made on the basis of a preference for a given triplet are also more implicit. Although we have found very little evidence for implicit knowledge in our work, this is nevertheless a possibility which should be addressed. Research in this area should develop a paradigm for the systematic study of the role of fluency in visual triplet learning, and how it is related to implicit and explicit knowledge.

7.7 A comparison of the visual and auditory modalities

As expected on the basis of the existing literature, in this thesis we have found larger learning effects for our auditory than visual tasks. This can be seen as supporting the idea that the Statistical Learning ability is dependent on modality of presentation (Siegelman & Frost, 2015), and that audition is the privileged modality for statistical learning, which is now widely accepted and backed up by large amounts of evidence in the field (see Siegelman et al. (2018) for a review). With the auditory scaffolding hypothesis, Conway & Kronenberger, (2010) put forward the idea that humans are hardwired to better extract regularities in the auditory modality, and that this provides a basis for a number of general cognitive abilities. To illustrate this point, language (Arciuli, 2018) and music (Rohrmeier & Rebuschat, 2012) are two glaring examples of auditory statistical learning in everyday use.

The auditory modality has also been shown to be more resilient to dual-task demands in statistical learning than the visual modality (Robinson & Sloutsky, 2013). We confirmed this with our findings of Chapter 2, which tested children on an auditory statistical learning task with a cover task, and Chapter 4, which used a visual statistical learning task with an equivalent cover task on adult participants. Despite this was not a direct comparison, we found evidence that, whilst the children's performance was not negatively affected by the presence of a dual task, the adults performed worse when the cover task was present than when it was not.

In regards to our main question of implicit and explicit knowledge in statistical learning, we observed more explicit knowledge, as well as greater consistency between our different measures of conscious knowledge, in the auditory than visual modality (Appendix H). This is a potentially important contribution to the understanding of implicit and explicit knowledge in classical statistical learning tasks. In fact, it supports our hypothesis put forward earlier on that, with a sufficiently large learning effect, knowledge in our statistical learning tasks results to be entirely explicit.

Another factor that may exacerbate the difference in performance between the visual and auditory modality is the lower test-retest reliability of the visual triplet learning task, compared to auditory triplet learning. Siegelman & Frost, (2016) compared reliability between a visual and an auditory Statistical Learning task, and found the *r* coefficient of reliability to be equal to 0.58 for visual Statistical Learning and equal to 0.6 for auditory Statistical Learning, whilst, a good *r* coefficient of reliability should be around 0.8. The data gathered in this thesis is consistent with these authors in providing an illustration of this fact. Our visual statistical learning effect of above-chance performance did not replicate between our EEG experiment in Chapter 6, in which performance was, on average, at chance, and our other visual statistical learning experiments. Furthermore, our work shows that the size of the learning effect in the visual triplet learning task is highly variable from one experiment to another. This is likely to reflect the low test-retest reliability of the task. Our work fits in, and agrees with, the most recent research in this area raising methodological concerns around the visual triplet learning task.

Low test-retest reliability is problematic for the development of visual statistical learning research and poses an obstacle for the investigations needed to answer a range of open questions in the area. Whilst, as Siegelman & Frost (2016) suggested, increasing the variety and amount of test items in the test phase could be beneficial in improving the test-retest reliability of the task, as discussed earlier on, this is a solution which presents a number of challenges around fatigue effects and potential within-test learning. These numerous concerns raise questions about the importance of the study of visual sequential statistical learning, and whether the visual triplet learning paradigm should be at all pursued by future research.

Research using the visual triplet learning paradigm originally aimed to assess whether findings of statistical learning only applied to the auditory modality (Hazan et al., 2008), or whether they could also be extended to the visual modality, therefore making statistical learning a domain-general ability. The question of the domain generality or specificity of statistical learning is an important one for the understanding of this ability, and an object of debate in the field, to date (Frost et al., 2015). It is important, for example, for research to be able to study transfer of statistical learning from the auditory to the visual modality, and vice-versa. This makes the question of developing suitable visual statistical learning paradigms relevant and worth pursuing.

7.8 Practical applications of our work

In this section we aim to provide an overview of areas for practical applications of our work, and make recommendations for future research efforts in this respect. This Thesis has shown that the PDP, guessing and zero correlation criteria can successfully be applied to measure implicit and explicit knowledge in statistical learning in both the visual and auditory modality. This opens up a number of possibilities for further research applied to real-life stimuli, such as natural language, in both typically and atypically developing populations.

Research has shown that statistical-learning based training is useful in improving spoken language outcomes in children with a language development delay (Deocampo, Smith, Kronenberger, Pisoni & Conway, 2018). To this existing research our work in our Thesis can contribute the methods that we have developed to facilitate the measurement of implicit and explicit knowledge. This will be important to understand the quality of the statistical learning and which component, implicit or explicit, contributes the most to the language improvement. In fact, although the idea that SL can be used to improve language function has recently become increasingly accepted in the literature (Conway, Gremp, Walk, Bauernschmidt & Pisoni, 2012), there is not much clarity regarding the individual roles of implicit and explicit knowledge in this. We regard this as an important research question, as it is possible that these two knowledge types may play a differential role in language learning.

Through our manipulations of implicit and explicit knowledge in Chapter 5 of this Thesis, we have found that a faster stimulus presentation promotes greater implicit knowledge in both the visual and auditory modality. Future research should aim to utilise this finding to develop an intervention in which different speeds of stimulus presentation can be used to enhance either implicit or explicit knowledge of stimuli, depending on what is needed. This could, for example, be trialled in the context of language learning. There are suggestions in the literature that learning implicitly, intended as the ability to encode structure without awareness, is key for language acquisition and language processing, in particular for what concerns word predictability, an ability which is crucial for speech perception, as it allows accurate understanding even in conditions of degraded speech (Conway, Bauernschmidt, Huang & Pisoni, 2010; Misyak, Christiansen & Tomblin, 2010). We see this as a fruitful area of application for our work. For example, the presentation speed of language stimuli could be used to potentiate implicit or explicit learning, and a combination of the two could be employed as necessary to maximise the learning effect.

Second language (L2) learning is also an important research area for the application of our findings, and research efforts devoted to the understanding of the roles of implicit and explicit knowledge are ongoing (Ishikawa, 2019). It emerges that more research in this area would be needed, specifically addressed at comparing implicit and explicit learning (DeKeyser, 2003). Future research will be able to incorporate the methods that we have developed in this Thesis by using the PDP in combination with the zero correlation and guessing criteria, and a generation task to assess the status of L2 knowledge. To the best of our knowledge, we are not aware of work which has used this combination of methods on real-life L2 stimuli. Work in this area will not only allow the identification of the most effective learning strategies for L2 acquisition, but we also believe that it will be an important step, building on existing research (Gasparini, 2004) towards developing L2 teaching practice which can maximise learning.

For example, there is evidence that awareness and explicit strategies play a positive role in L2 learning (DeKeyser, 2003). Our work could be used in this field for the purpose of enhancing learning of a second language. In fact, we have found that knowledge of salient items, or chunks, in our visual statistical learning paradigm was held more explicitly, as participants were better able to reproduce these fragments in a generation task. Although the roots of the triplet preference effect observed in this Thesis will need to be investigated further, this knowledge could be used for the development of a language-learning training program aimed at enhancing explicit learning of specific linguistic items by making them more salient and by facilitating associations with other concepts, using a similar mechanism to that driving the triplet preference effect that we observed.

Finally, a promising research area which is currently under-investigated is the use of implicit and explicit learning strategies in atypically developing populations. For example, not much research exists on implicit and explicit learning in individuals with Autistic Spectrum Disorder (ASD). By providing an effective method for measuring the status of knowledge, our work opens up possibilities in this area. A question of interest is whether individuals with ASD make more use of implicit or explicit knowledge. Research in this area has shown that individual with ASD have a tendency to underuse implicit processes in learning, and compensate by employing more effortful explicit strategies instead for tasks that typically developing children resolve through implicit strategies (Pérez, González, Llorente Comí & Nieto, 2007, p. 83).

Given that implicit learning is crucial for the development of important cognitive functions, such as language skills and various aspects of social development (Pérez, et al., 2007, p. 84), it is crucial for research to develop ways in which this can be improved in children with ASD. This leads to another interesting avenue for research, and application of our work in this Thesis. Future efforts in this area should aim to develop ways in which the use of implicit knowledge can be maximised. Our data in this Thesis indicate that altering stimulus presentation speed affects the amount of implicit knowledge developed, with faster speed leading to higher implicit knowledge. However, future research may discover more methods in which the use of implicit knowledge can be maximised. These types of applications of our work would not only yield immediate benefits, but also encourage the development of new research in this unexplored area.

7.9 Conclusions and directions for future research

This thesis has built on, and extended, the existing literature in a complex area of research. When examining this field, a consistent picture emerges, which the present work confirms, that there is not yet agreement over the most suitable theoretical and experimental framework within which the statistical learning phenomenon more generally, and, specifically, the question of implicit and explicit knowledge, are to be situated. Therefore, based on the existing literature in this area, and the findings of this thesis, the next question to ask is what approaches future research should take in order to advance knowledge about statistical learning, and about the type of knowledge acquired as a result of this process.

A promising next step is to further investigate the source of individual variability in statistical learning tasks. The present work did not directly aim to address this question which, however, remains important for the study the statistical learning ability more widely. Concerns have also been raised around the difficulty that the low reliability of classical statistical learning tasks poses for the study of individual differences. Siegelman et al., (2017) have pointed out that the majority of participants in statistical learning tasks performs around chance level, something which our work has confirmed. As variation in performance for these at-chance participants is very probably a product of guessing and noise, it does not provide reliable information for the purpose of computing correlations with other cognitive measures. In future work, we aim to clarify why the majority of participants perform around chance level, with a small number of good performers. Our lack of significant correlations between forced-choice task performance and musical sophistication, working memory and NART scores could either be due to our choice of cognitive measures or, as Siegelman et al., (2017) suggested, to the fact that the majority of our participants performed around chance level. In agreement with Siegelman et al., (2017), we hold that it would be beneficial if research in this area shifted its focus from the assessment of performance through measures of central tendency and, instead, concentrated on understanding the sources of individual variability in participants' performance. This is essential for the understanding of the statistical learning ability and its underpinnings and, as a consequence, will also facilitate investigations on implicit and explicit knowledge in this type of learning.

The field would benefit from a shift in approach from behavioural to neuropsychological methods. For example, given that Statistical Learning comprises a variety of different computations, it would be useful for research to understand how different brain networks operate together to process the different types of statistics present in the input, and how these networks change their configuration depending on different types of statistics in the input (Hasson, 2017). In fact, as this work has confirmed, behavioural methods are heavily dependent on participant strategies for performance, and do not allow to easily tease apart the range of different types of information used by participants. The development of this new type of knowledge will only be made possible by a neuropsychological approach. Specifically, we propose that the use of EEG will be crucial in studying the distribution of activation and cooperation between different brain areas through the observation of neural oscillations related to the processing of a variety of statistics present in the input.

This thesis, similarly to previous research in this area, has approached the question of implicit and explicit knowledge in statistical learning with the aim to attempt to distinguish the two based on the outcome they produce, that is, whether participants, after learning, are conscious of the acquired knowledge. Through our work, we have confirmed that this approach presents a number of challenges, and we suggest that future research should explore alternative conceptualisations for this question. For example, Henke (2010) has proposed a processes-based approach, which focuses on the types of processes taking place the memory system to distinguish between implicit and explicit memory, rather than on conscious awareness, that is, whether the knowledge of something is unconscious or not. This proposal echoes older suggestions (Stadler, M.A., Frensch, 1994) that a definition of "implicit" based on the lack of participants' intention to learn, that is, on the learning process, rather than on awareness, can be operationalised more easily. Such a framework based on the processes which take place during learning is crucially dependent on methodologies which allow to measure learning as it happens, and therefore predicated on the use of neuropsychological techniques, such as EEG, and fMRI to study the different brain networks involved in implicit and explicit processes.

Future research should also make wider use of connectionist approaches, which seem a promising avenue in understanding the difference in processing between conscious and unconscious. Such approaches are also focused on the processes that take place in the brain, rather than the outcomes of learning, as their goal is to understand how implicit and explicit processing differ in terms of the computations they involve (Cleeremans, 2014). Computational modelling makes it possible to focus on the mechanisms through which conscious processing occurs, therefore allowing to bypass the methodological constraints of behavioural research, and the challenges of measuring learning as it happens. Furthermore, it also offers the possibility of modelling meta-cognition, or interactions of the brain with itself, explaining how brain changes occur as a result of such interaction (Cleeremans, 2014). Therefore, the study and implementation of the process of meta-cognition, or consciousness, can occur with high precision in a way that the behavioural approach does not allow.

Together with emerging research in this area, this thesis is one of the first few experimental pieces of work to shed light on the theoretical and methodological challenges inherent to the behavioural approach, which stand in the way of clarifying the question of implicit and explicit knowledge in statistical learning. In fact, through our work, we have confirmed that such challenges currently prevent us from firmly answering the question of implicit and explicit knowledge in statistical learning. We have found that knowledge acquired through classical statistical learning paradigms, and assessed through behavioural measures, is mostly explicit, and we have put forward the hypothesis that knowledge measured in this way will become more explicit, the greater the learning effect. Our work has confirmed that the question of implicit and explicit knowledge in statistical learning is highly complex, as it requires us to confront two large theoretical challenges which, research, to date, has not yet resolved: one revolves around better understanding the statistical learning ability itself, and the other is arriving at a conceptualisation of implicit and explicit knowledge which can allow successful investigations. We propose that statistical learning research is only just beginning to understand more about these complex problems and that, with the aid of neuropsychological approaches, which will allow research to surpass the shortcomings of behavioural investigations, new solutions will continue to develop.

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Appendices

Appendix A: Ethical approval information

Ethical approval form

Ethical approval granted on the basis of the form below applies to all experimental work done for this PhD.

SCHOOL OF PSYCHOLOGY ETHICAL APPROVAL FORM FOR HUMAN PARTICIPANTS

Tick relevant boxes: ☐ STAFF Project ✓ POSTGRADUATE Project ✓ TRACK A
☐ UNDERGRADUATE Project ☐ TRACK B
☐ ROUTINE EXTENSION TO STUDY

Title Of Project: *~~Sequential regularities learning: The nature of the acquired~~ knowledge and the role of explicit and implicit processes.*

Name of researcher(s) Federica Menchinelli

Name of supervisor (for student research) Dr Simon Durrant; Dr Petra Pollux
Date 27/07/2015

		YES	NO	N/A
1	Will you describe the main procedures to participants in advance, so that they are informed in advance about what to expect?	✓		
2	Will you tell participants that their participation is voluntary?	✓		
3	Will you obtain written consent for participation?	✓		
4	If the research is observational, will you ask participants for their consent to being observed / taped?			✓
5	Will you tell participants that they may withdraw themselves or their data from the research at any time, that no reason needs to be given, and that they can do so without losing any rewards (if applicable)?	✓		
6	Will you give participants the option of declining to give information they do not want to give (e.g., not filling out all questions in a questionnaire)?	✓		
7	Will you tell participants that their data will be treated with full confidentiality, and stored securely (for 7 years at the minimum) and that, if published, it will not be identifiable as theirs?	✓		
8	Will you debrief participants at the end of their participation (i.e. give them a brief explanation of the study)?	✓		

If you have ticked **No** to any of Q1-8, but have **ticked box A** overleaf, please give any explanation on a separate sheet. (Note: N/A = not applicable)

		YES	NO	N/A
9	Will your project involve deliberately misleading participants in any way?		✓	
10	Is there a realistic risk of any participants experiencing either physical or psychological distress or discomfort? If **Yes,** give details on a separate sheet and state what you will tell them to do if they should experience any problems (e.g. who they can contact for help).		✓	

If you have ticked **Yes** to 9 or 10 you should normally **tick box B** overleaf; if not, please give a full explanation on a separate sheet.

			YES	NO	N/A
11	Do participants fall into any of the following special groups? If they do, please refer to the appropriate BPS guidelines, and **tick box B** overleaf. **Please note that you may also need to gain satisfactory CRB clearance or equivalent for overseas participants.**	School children (under 18 years of age)		✓	
		People with learning or communication difficulties		✓	
		Patients		✓	
		Those at risk of psychological distress or otherwise vulnerable		✓	
		People in custody		✓	
		People engaged in illegal activities (e.g. drug taking)		✓	

There is an obligation on the lead researcher to bring to the attention of the School's Ethics Committee projects with ethical implications not clearly covered by the above checklist.

PLEASE TICK **EITHER** BOX A or BOX B BELOW AND **PROVIDE THE DETAILS REQUIRED** IN SUPPORT OF YOUR APPLICATION, THEN SIGN THE FORM.

Please tick:

A. I consider that this project has **no** significant ethical implications to be brought before the Departmental Ethics Committee.	✓

In less than 150 words, provide details of the study including the rational, the number and type of participants, methods and tests to be used (i.e. the procedure).

This series of studies aims to further the understanding of mechanisms of learning of sequential regularities and the roles of explicit and implicit knowledge. This type of learning will be assessed in undergraduate students through the use of sequences of visual shapes and tones which will be constructed to contain statistical regularities. The experimental paradigm will first consist of an acquisition phase where participants, uninformed of the presence of regularities, will be exposed to the stimuli for a maximum of 30 minutes. This will be followed by a test phase, where participants' implicit and explicit knowledge of the sequence structure will be assessed by either asking participants to generate, or avoid generating, fragments of the learned sequences, or alternatively by asking participants to choose which of two sequence fragments is known, and obtaining confidence and knowledge attribution ratings. One study will investigate the neural correlates of implicit and explicit knowledge by using the above mentioned behavioural methods in combination with EEG (electroencephalogram).

This form (and any attachments) should be submitted to the school's Ethics Committee where it will be considered by the Chair before it can be approved.

B. I consider that this project **may** have ethical implications that should be brought before the Departmental Ethics Committee, and /or it will be carried out with children or other vulnerable populations.	

Please provide details of the project on an EA2 University Ethics for Human Participants taking into account the following advice:

1. Be clear about the purpose of the project and its academic rationale.
2. Briefly describe the methods / measurements and parties involved / affected.
3. Be clear about recruitment methods, numbers used, age, gender, exclusion/inclusion criteria, handling procedures for field experiments, etc.
4. Include concise statements of the ethical considerations raised by the project (including care and aftercare) and how you intend to deal with them.
5. Include all relevant materials, such as consent form, participant information form, debrief, questionnaire / stimulus materials, letters /posters to recruit, etc.

This form should be submitted to the School's Ethics Committee for consideration.
If any of the above information is missing, your application will be returned to you.

I am familiar with the BPS Guidelines for ethical practices in psychological research, and the University Regulations for Ethical Research (and have discussed them with other researchers involved in the project or my supervisor)

Signed... Print Name.. Date...............
(UG/PG Researcher(s), if applicable) Email...

Signed... Print Name.. Date.............
(Lead Researcher or Supervisor) Email...

STATEMENT OF ETHICAL APPROVAL

There is an obligation on the lead researcher to bring to the attention of the School's Ethics Committee projects with ethical implications not clearly covered by the above checklist.

PLEASE TICK **EITHER** BOX A or BOX B BELOW AND **PROVIDE THE DETAILS REQUIRED** IN SUPPORT OF YOUR APPLICATION, THEN SIGN THE FORM.

Please tick:

A. I consider that this project has **no** significant ethical implications to be brought before the Departmental Ethics Committee.	✓

In less than 150 words, provide details of the study including the rational, the number and type of participants, methods and tests to be used (i.e. the procedure).

This series of studies aims to further the understanding of mechanisms of learning of sequential regularities and the roles of explicit and implicit knowledge. This type of learning will be assessed in undergraduate students through the use of sequences of visual shapes and tones which will be constructed to contain statistical regularities. The experimental paradigm will first consist of an acquisition phase where participants, uninformed of the presence of regularities, will be exposed to the stimuli for a maximum of 30 minutes. This will be followed by a test phase, where participants' implicit and explicit knowledge of the sequence structure will be assessed by either asking participants to generate, or avoid generating, fragments of the learned sequences, or alternatively by asking participants to choose which of two sequence fragments is known, and obtaining confidence and knowledge attribution ratings. One study will investigate the neural correlates of implicit and explicit knowledge by using the above mentioned behavioural methods in combination with EEG (electroencephalogram).

This form (and any attachments) should be submitted to the school's Ethics Committee where it will be considered by the Chair before it can be approved.

B. I consider that this project **may** have ethical implications that should be brought before the Departmental Ethics Committee, and /or it will be carried out with children or other vulnerable populations.	

Please provide details of the project on an EA2 University Ethics for Human Participants, taking into account the following advice:

1. Be clear about the purpose of the project and its academic rationale.
2. Briefly describe the methods / measurements and parties involved / affected.
3. Be clear about recruitment methods, numbers used, age, gender, exclusion/inclusion criteria, handling procedures for field experiments, etc.
4. Include concise statements of the ethical considerations raised by the project (including care and aftercare) and how you intend to deal with them.
5. Include all relevant materials, such as consent form, participant information form, debrief, questionnaire / stimulus materials, letters /posters to recruit, etc.

This form should be submitted to the School's Ethics Committee for consideration.
If any of the above information is missing, your application will be returned to you.

I am familiar with the BPS Guidelines for ethical practices in psychological research, and the University Regulations for Ethical Research (and have discussed them with other researchers involved in the project or my supervisor)

Signed........ Print Name FEDERICA MENCHINELLI Date 28/07/2015
(UG/PG Researcher(s), if applicable) Email fmenchinelli@lincoln.ac.uk

Signed S. J. Durrant Print Name SIMON DURRANT Date 28/7/2015
(Lead Researcher or Supervisor) Email SDurrant@lincoln.ac.uk

STATEMENT OF ETHICAL APPROVAL

Appendix B – Chapter 2 additional information

B.1 Auditory statistical learning in adults: participant information sheet, consent form and debrief

A pilot investigation into the mechanisms of auditory sequence processing.

Information sheet

Thank you for your interest in this study.

We aim to investigate the processing of auditory stimuli in a computer- based experiment which will consist of two parts. In the first part you will be asked to simply listen to a series of tones played through headphones. In the second part you will be asked to listen to a shorter series of tones and will be asked some simple questions about them.

The experiment should take no longer than 45 minutes overall and you will be granted 3 credit points for your participation.

All the information collected about you for the purpose of this study will be anonymised and kept confidential. Please remember that you have the right to withdraw your data from the study at a later stage, should you wish to do so. Please remember that you have the right to withdraw from this study at any point without providing any motivation.

This study is part of a PhD project conducted by Federica Menchinelli (fmenchinelli@lincoln.ac.uk) under the supervision of Dr Simon Durrant (sidurrant@lincoln.ac.uk) and Dr Petra Pollux (ppollux@lincoln.ac.uk).

The study has received ethical clearance by the School of Psychology Research Ethics Committee (University of Lincoln). If you have any queries about the research ethics, please contact SOPREC (School of Psychology Research Ethics) soprec@lincoln.ac.uk.

A pilot investigation into the mechanisms of auditory sequence processing.

Consent Form

Please indicate whether you consent to taking part in this study by answering the questions below:

- I have read and understood the participant information sheet **Yes/ No**
- I confirm that I am eligible to take part in this study **Yes/ No**
- I have had the opportunity to ask any questions **Yes/ No**
- My questions have been answered satisfactorily **Yes/ No**
- I understand that:

  I am free to withdraw from the study at any time and without having to provide a reason **Yes/ No**

  All the information collected about me will be anonymised and kept confidential **Yes/ No**

- I agree to take part in this study **Yes/ No**

I agree to take part in this computer-based study. This will involve listening to sequences of tones played through headphones and answering some questions. I will be granted 3 credit points for my participation.

Signed (participant) ______________________________

Signed (researcher) ______________________________

Date ________________

This study is part of a PhD project conducted by Federica Menchinelli (fmenchinelli@lincoln.ac.uk) under the supervision of Dr Simon Durrant (sidurrant@lincoln.ac.uk) and Dr Petra Pollux (ppollux@lincoln.ac.uk).

The study has received ethical clearance by the School of Psychology Research Ethics Committee (University of Lincoln). If you have any queries about the research ethics, please contact SOPREC (School of Psychology Research Ethics) soprec@lincoln.ac.uk.

A pilot investigation into the mechanisms of auditory sequence processing.

Participant Debrief

Thank you for your participation.

This experiment has tested your learning of auditory sequences with a regular structure (sequential regularities learning). Our aim is to understand the roles of implicit (unconscious) and explicit (conscious) knowledge in this type of learning.

To distinguish your implicit and explicit knowledge of the sequence we have used a well-established test called the Process Dissociation Procedure (PDP). This test has never been previously used with auditory stimuli, therefore the aim of this pilot study was to evaluate its suitability.

In the second part of the experiment you were asked to either choose the correct fragment of tone sequences (inclusion instructions) or to avoid choosing the correct fragment of tone sequences (exclusion instructions). Under inclusion instructions your performance could be influenced by both implicit and explicit knowledge while exclusion performance requires explicit knowledge: you need to be conscious of knowing parts of the sequence to the able to avoid generating them.

We aim to evaluate whether PDP can discriminate between explicit and implicit knowledge when used with sequences of tones. The result of this experiment will be of crucial importance for the planning of future investigations of explicit and implicit knowledge in sequential regularities learning.

This study is part of a PhD project conducted by Federica Menchinelli (fmenchinelli@lincoln.ac.uk) under the supervision of Dr Simon Durrant and Dr Petra Pollux.

For further questions contact: Federica Menchinelli (fmenchinelli@lincoln.ac.uk).

B.2 Auditory statistical learning in children

B.2.1 Summer Scientist Week ethics application and study information forms

Summer Scientist Week Experiment Information

Please complete the two following forms.

Form 1 will provide us with all the information we need to organise and advertise the summer scientist week. It also includes a declaration for you to sign.

Form 2 will provide us with all the information we need to get ethical approval. All studies that will run during the summer scientist week will be submitted into a single and joined ethical application.

<u>FORM 1: practical information</u>

1. Name of the person who will be collecting the data	Federica Menchinelli ; Hannah Silcox-Crowe
2. Supervisor (if relevant)	Dr Simon Durrant ; Dr Petra Pollux
3. Study title (in scientific terms) Implicit and explicit processes in children’s auditory statistical learning.	

4. Age range of participants (between 3 - 10 years)	8-10 years
5. Number of participants tested at a time	20
6. How long will your study take to run with each participant?	15 minutes

7. Please give brief details of the type of activities your study (e.g. making decisions about stimuli presented on a computer)**.**

There will be three types of activities involved in the study

1) Listening to a series of musical tones through headphones whilst responding (through a keypress) to tones with a different timbre which sound at random points within the musical stream.
2) Completing a two-alternative-forced-choice task testing discrimination of previously heard tone sequences from unheard tone sequences.
3) On each trial of the forced-choice task, providing a confidence rating on a binary scale ("know"/ "guess")

8. How much space do you need to run the study?

A very small room would be sufficient. No special equipment is needed other than a computer.

9. Does the study involve any noisy activities (e.g. running, playing sounds etc.) that would disturb other studies happening in the same room?

No, the study does not involve sound. All noise will be limited to conversation between the researcher and the participant. It will be necessary for participants to concentrate, as these tasks will measure learning and response times, therefore any excessively noisy activities taking place in the same room might be disruptive for this experiment.

10. Are there any activities that might provide specific Health & Safety concerns?

No, all the activities involved in this experiment are safe.

11. What furniture do you need (e.g. one child-sized table and two child-sized chairs plus a larger chair for an accompanying parent)?

The experiment will run on a laptop. A table and chair will be needed for children to sit comfortably at the laptop, plus one extra chair for an accompanying parent.

12. What equipment do you need (including sockets)? Please clearly indicate what equipment you will provide and what you expect us to provide. Please note that we cannot provide you with specialist equipment.

We will provide a laptop to run the experiment. In the testing room there will need to be one plug socket for the laptop, as well as basic furniture (a table and a chair for the participant to sit). We will also provide headphones for the participants to wear.

13. What participant restrictions do you have (e.g. gender restrictions, can you test children with special education needs or developmental disorders)?

We are looking for both males and females aged 8-10 years. We would like to exclude children with special education needs or any developmental disorders which might affect their learning abilities.

14. Does the study involve any questionnaires to be completed by the parent? If yes, please describe.

There will be a very brief questionnaire to be completed by parents. This will contain a few very simple questions relating to their child's musical abilities and musical training, as well as an indication of preferred subjects at school. **15. Do you have any publications relevant to this project? If yes, please name them.** I have not published any papers relevant to this project.

16. Does the person testing already have DBS clearance from the University? **If not, please provide their email address**	The last time I obtained DBS clearance from the University was for SSW in 2017. My email address is fmenchinelli@lincoln.ac.uk I believe our research assistant, Hannah Silcox-Crowe, has also obtained clearance when working in SSW last year. Her email address is 11247125@students.lincoln.ac.uk

17. Your study will need to be presented in lay terms in the consent form and advertisement materials. See last year's consent form here attached for some examples. Based on those examples: **Please provide a funny title for your study which should be framed as a "game":** Musical notes **Please provide a brief description of your study suitable for parents (around 100 words). Avoid words like experiment, stimuli, and any specialist terms.**

We are interested in children's ability to learn specific sequences of sounds. Your child will be asked to play a game involving familiarisation with, and recognition of, different musical sequences.

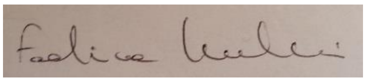
We will first ask your child to listen to a long sequence of notes. Occasionally, a note from a different musical instrument will sound and your child will be asked to detect it as quickly as possible by pressing a key. This is so that your child can become familiar with the sequence of notes. After this, we will play a memory game where your child will be asked which of two sequences of notes sounds familiar to him/her, and how confident they are in their responses. Overall, the session will take no longer than 15 minutes. The results of these tasks will help us understand more about how children's learning and memory work.

Thank you for your help!

I confirm that by registering for the Summer Scientist Week 2018 I am giving full commitment to the dates 20th – 24th August 2018 inclusive.

Despite any changes to my project before and/or during the event I will be available and committed to contributing to the event.

Activities may include planning and promoting the event, providing games/activities with the participants, writing a post-event report for the Newsletter.

Signature:		Date:	21/05/2018

FORM 2: ethical application

Please read carefully the following notes:

The information provided on this form will form the basis of a joint ethics application submitted for all studies running as part of the Summer Scientist Week. Please fill out all sections of the form, even if you have already received ethical clearance for your study.

There is no need to provide your own information sheet and consent form. Parents will receive a single information sheet with details of all studies (see last year's example) and one consent form. This will allow them to opt out of particular studies if desired.

All children will be presented with a gift pack before they leave including a certificate, pencil and t-shirt/baseball cap, therefore it is not necessary to provide rewards for individual studies.

IMPORTANTLY, it will not be possible to amend the ethics application once it has been submitted, therefore if possible please ensure that the information you provide will cover any small changes (not affecting the ethical concerns) that may need to be made at a later date.

Has this study received ethical clearance (please tick all that apply):

a) **yes, from SOPREC for the use with children of this age group ___**
b) **yes, as part of previous SSW events in Lincoln ___**
c) **yes, from SOPREC for the use with students _X_**
d) **yes, from SOPREC for the use with other groups ___**
e) **yes, from elsewhere (please briefly specify) ___**

Do you need to run any standardised tests with your study, e.g. language development?

a) **yes ___**
Please state which tests and whether you will run them

b) no __X**_**

Study Description – Rationale

Statistical learning is our ability to extract underlying regularities from statistically structured stimuli. This project aims to understand the extent to which implicit and explicit knowledge are acquired as a result of statistical learning in children. The data collected will be compared to adult data with the aim to compare the use of implicit and explicit knowledge in statistical learning between age groups.

Procedure

We will make use of a well-known auditory transition matrix paradigm (Durrant et al., 2011, 2013) consisting of presentation of a stream of tones which, unknown to the participant, follow an underlying statistical structure. Although adult participants have shown an ability to learn the statistical structure present in these tone sequences (Durrant et al., 2011, 2013), the transition matrix paradigm has never been used with children. Studies on auditory statistical learning in infants (Saffran et al., 1999) and children (Evans et al., 2009), however, suggest that children may be able to learn the underlying statistical structure of the stimuli, and would therefore be able to discriminate learned tone sequences from unheard tone sequences in a subsequent forced-choice test. Following the methodology that we have previously used with adults, the first phase of our experiment (familiarisation) will involve children listening to a long sequence of tones played through headphones for approximately five minutes. To ensure continued attention, children will be given a cover task involving detection of a tone with a different timbre played at random points in the exposure stream. This will be followed by an objective assessment of learning of the statistical structure through a two-alternative forced-choice task: children will be presented with two tone sequences (one belonging to the exposure stream and one new, unheard, sequence) and will be asked to choose which one sounds more familiar to them. Binary confidence judgments (guess/ remember) will be collected on a trial-by-trial basis for a subjective assessment of confidence. The experiment will take approximately 15 minutes to complete.

Age of participants **(note:** It will only be possible to test the age groups you have ethical permission for, therefore please include any age groups you may be likely to test as it will not be possible to amend the ethics application at a later date.)

8-10 years

Please provide in appendix any written experimental materials if relevant (e.g. questionnaires).

Please see Appendix A

Specific Ethical Concerns

You do not need to explain participants tested outside the school, participants under or participants recruited from special sources as these apply to all studies and will be covered in the general application.

There are no specific ethical concerns associated to this project. The auditory stimuli will be simple sequences of tones, and the volume will be adjusted to a level that is comfortable for the child. The duration of individual tasks will not be excessive: five minutes for the exposure phase and 10 minutes for the two-alternative forced-choice task). Participants will be free to leave the study at any time, should they wish to do so.

Appendix A

Questionnaire for parents

SECTION 1

General information

What is your child's age? ________________________

What academic year has your child just completed? ____________________

SECTION 2

We are interested in your child's musical abilities because these have been found to correlate with the ability to learn the structure of visual and auditory stimuli.

Below are a few quick questions on your child's level of musical training. Please circle to indicate your chosen answer:

- Your child has been complimented for his/her talents as a musical performer.

1 Completely Disagree	2 Strongly Disagree	3 Disagree	4 Neither Agree nor Disagree	5 Agree	6 Strongly Agree	7 Completely Agree
1	2	3	4	5	6	7

- Your child has engaged in regular, daily practice of a musical instrument for how many years?

0 / 1 / 2 / 3 / 4-5 / 6-9 / 10 or more years.

- At the peak of his/her interest, how many hours per day did/does your child practice on his/ her primary instrument?

0 / 0.5 / 1 / 1.5 / 2 / 3-4 / 5 or more hours

- Your child has had formal training in music theory for how many years?

0 / 0.5 / 1 / 2 / 3 / 4-6 / 7 or more years.

- How many years of formal training on a musical instrument (including voice) has your child had?

0 / 0.5 / 1 / 2 / 3-5 / 6-9 / 10 or more years

- How many musical instruments can your child play?

0 / 1 / 2 / 3 / 4 / 5 / 6 or more musical instruments.

SECTION 3

The ability to understand the structure of sequences of stimuli could relate to several other abilities. We are interested in finding out more and, for this reason, we would like to ask you some questions about your child's preference for certain school subjects and their performance in those subjects.

Please indicate your response to the questions below. Feel free to skip any questions that you do not wish to answer:

On a scale from 1 to 10, how would you rate your child's performance, compared to other children in his/ her class, on the following subjects?

Mathematics 1 2 3 4 5 6 7 8 9 10

English 1 2 3 4 5 6 7 8 9 10

Science 1 2 3 4 5 6 7 8 9 10

Foreign languages (if applicable) 1 2 3 4 5 6 7 8 9 10

Art (if applicable) 1 2 3 4 5 6 7 8 9 10

How would you rate your child's enjoyment of the following subjects?

Mathematics 1 2 3 4 5 6 7 8 9 10

English 1 2 3 4 5 6 7 8 9 10

Science 1 2 3 4 5 6 7 8 9 10

Foreign languages (if applicable) 1 2 3 4 5 6 7 8 9 10

Art (if applicable) 1 2 3 4 5 6 7 8 9 10

B.2.2 Additional information for parents

Musical notes - Further information for parents

Implicit and explicit processes in children's auditory statistical learning.

Statistical learning is our ability to extract underlying regularities from statistically structured stimuli. This project aims to understand the extent to which implicit (unconscious) and explicit (conscious) knowledge are acquired as a result of statistical learning in children.

We are making use of a well-known auditory statistical learning paradigm (Durrant et al, 2011) consisting of presentation of a sequence of tones which, unknown to the participant, follows a specific structure. Previous research has shown that adults have an ability to learn this structure and therefore can discriminate learned tone fragments from previously unheard tone fragments in a subsequent forced-choice test. However, we still do not know whether children are able to learn this tone structure, and whether the knowledge they acquire in this task is conscious or unconscious.

The first phase of the experiment aims to familiarise children with the sequence of tones. A two-alternative forced-choice task is used after this is to assess learning of the tone structure. Both conscious and unconscious knowledge could contribute to performance in this task. Children are also asked if they are guessing or remembering: good performance on trials when children are claiming to be guessing is taken as an indication of unconscious knowledge.

The data collected will be compared to adult data, aiming to better understand how this type of auditory statistical learning works in different age groups.

Statement of ethical approval

All the information collected about your child for the purpose of this study will be anonymised and kept confidential. Please remember that you have the right to withdraw your child's data from the study at a later stage, should you wish to do so. Your child can withdraw from the study at any point if he/ she wishes.

This study has received ethical clearance by the School of Psychology Research Ethics Committee (University of Lincoln). If you have any queries about the research ethics, please let the researcher know.

Musical notes

What does this game involve?

We are interested in children's ability to learn specific sequences of notes. Your child will be asked to play a game involving familiarisation with, and recognition of, different sound sequences.

We will first play an audio of a long sequence of notes. Occasionally, some of the notes will play in a different musical instrument and your child will be asked to detect these notes as quickly as possible by pressing a key. This is so that your child can become familiar with the sequence of notes. After this, we will play a memory game where your child will be asked which of two sequences of notes sounds familiar to him/her, and whether their response was a guess or not. Overall, the game will take no longer than 15 minutes.

The results obtained will help us understand more about how children's learning and memory work. Thank you for your help!

B.2.3 Musical notes: full task instructions

Instructions were displayed on the computer screen as part of the experiment and read out loud by the experimenter. Any other clarifications were given verbally, if needed.

Exposure instructions

Instructions (1)

In the next four minutes you will hear a sequence of different musical notes. Your task is to listen to these notes. But be careful! because some of the notes want to be different from the others and they will change the way they sound! Can you spot all the different-sounding notes? Quickly press the space bar as soon as you hear one!

Practice instructions

I will first show you \n what the different-sounding notes sound like....

Instructions (2)

Are you ready for the real game?

End of exposure message

Well done! You have completed the first part of the game.

Two-alternative forced-choice task instructions

Instructions (1)

I will tell you a secret about the musical notes you just heard: they always followed each other in a specific order! I will play two short note sequences. Can you tell me which of the two sounds more familiar?

Choice instructions

1 = Sequence 2 sounds MORE FAMILIAR

2 = Sequence 2 sounds MORE FAMILIAR

Knowledge attribution instructions

Did you guess or did you remember?

1 = GUESS

2 = REMEMBER

End of experiment instructions

Well done! This is the end of the game

B.2.4 Questionnaire for parents

<u>Musical notes - Questionnaire for parents</u>

SECTION 1

General information

What is your child's age? ________________________

What academic year has your child just completed? ___________________

SECTION 2

We are interested in your child's musical abilities because these have been found to correlate with the ability to learn the structure of visual and auditory stimuli.

Below are a few quick questions on your child's level of musical training. Please circle to indicate your chosen answer:

- Your child has been complimented for his/her talents as a musical performer.

1 Completely Disagree	2 Strongly Disagree	3 Disagree	4 Neither Agree nor Disagree	5 Agree	6 Strongly Agree	7 Completely Agree
1	2	3	4	5	6	7

- Your child has engaged in regular, daily practice of a musical instrument for how many years?

0 / 1 / 2 / 3 / 4-5 / 6-9 / 10 or more years.

- At the peak of his/her interest, how many hours per day did/does your child practice on his/ her primary instrument?

  0 / 0.5 / 1 / 1.5 / 2 / 3-4 / 5 or more hours

- Your child has had formal training in music theory for how many years?

  0 / 0.5 / 1 / 2 / 3 / 4-6 / 7 or more years.

- How many years of formal training on a musical instrument (including voice) has your child had?

  0 / 0.5 / 1 / 2 / 3-5 / 6-9 / 10 or more years

- How many musical instruments can your child play?

  0 / 1 / 2 / 3 / 4 / 5 / 6 or more musical instruments.

SECTION 3

The ability to understand the structure of sequences of stimuli could relate to several other abilities. We are interested in finding out more and, for this reason, we would like to ask you some questions about your child's preference for certain school subjects and their performance in those subjects.

Please indicate your response to the questions below. Feel free to skip any questions that you do not wish to answer:

On a scale from 1 to 10, how would you rate your child's performance, compared to other children in his/ her class, on the following subjects?

Mathematics 1 2 3 4 5 6 7 8 9 10

English 1 2 3 4 5 6 7 8 9 10

Science 1 2 3 4 5 6 7 8 9 10

Foreign languages (if applicable) 1 2 3 4 5 6 7 8 9 10

Art (if applicable) 1 2 3 4 5 6 7 8 9 10

How would you rate your child's enjoyment of the following subjects?

Mathematics 1 2 3 4 5 6 7 8 9 10

English 1 2 3 4 5 6 7 8 9 10

Science 1 2 3 4 5 6 7 8 9 10

Foreign languages (if applicable) 1 2 3 4 5 6 7 8 9 10

Art (if applicable) 1 2 3 4 5 6 7 8 9 10

B.3 Visual Statistical Learning: Piloting the transition matrix paradigm. participant information sheet, consent form and debrief

A pilot investigation into the mechanisms of visual sequence processing.

Information sheet

Thank you for your interest in this study.

We aim to investigate the processing of visual stimuli in a computer- based experiment which will consist of two parts. In the first part you will be asked to simply watch to a series of shapes displayed on the computer monitor. In the second part you will be asked to watch a shorter series of shapes and will be asked some simple questions about them.

The experiment should take no longer than 30 minutes overall and you will be given £5 for your participation.

All the information collected about you for the purpose of this study will be anonymised and kept confidential. Please remember that you have the right to withdraw your data from the study at a later stage, should you wish to do so. Please remember that you have the right to withdraw from this study at any point without providing any motivation.

This study is part of a PhD project conducted by Federica Menchinelli (fmenchinelli@lincoln.ac.uk) under the supervision of Dr Simon Durrant (sidurrant@lincoln.ac.uk) and Dr Petra Pollux (ppollux@lincoln.ac.uk).

The study has received ethical clearance by the School of Psychology Research Ethics Committee (University of Lincoln). If you have any queries about the research ethics, please contact SOPREC (School of Psychology Research Ethics) soprec@lincoln.ac.uk.

A pilot investigation into the mechanisms of visual sequence processing.

Consent Form

Please indicate whether you consent to taking part in this study by answering the questions below:

- I have read and understood the participant information sheet **Yes/ No**
- I confirm that I am eligible to take part in this study **Yes/ No**
- I have had the opportunity to ask any questions **Yes/ No**
- My questions have been answered satisfactorily **Yes/ No**
- I understand that:

  I am free to withdraw from the study at any time and without having to provide a reason **Yes/ No**

  All the information collected about me will be anonymised and kept confidential **Yes/ No**

- I agree to take part in this study **Yes/ No**

I agree to take part in this computer-based study. This will involve watching sequences of shapes displayed on the computer monitor and answering some questions. I will be given £5 for my participation.

Signed (participant) ______________________________

Signed (researcher) ______________________________

Date ________________

This study is part of a PhD project conducted by Federica Menchinelli (fmenchinelli@lincoln.ac.uk) under the supervision of Dr Simon Durrant (sidurrant@lincoln.ac.uk) and Dr Petra Pollux (ppollux@lincoln.ac.uk).

The study has received ethical clearance by the School of Psychology Research Ethics Committee (University of Lincoln). If you have any queries about the research ethics, please contact SOPREC (School of Psychology Research Ethics) soprec@lincoln.ac.uk.

A pilot investigation into the mechanisms of visual sequence processing.

Participant Debrief

Thank you for your participation.

This experiment has tested your learning of visual sequences with a regular structure (sequential regularities learning). Our aim is to understand the roles of implicit (unconscious) and explicit (conscious) knowledge in this type of learning.

To distinguish your implicit and explicit knowledge of the sequence we have used a well-established test called the Process Dissociation Procedure (PDP). This test has never been previously used with sequentially presented visual stimuli, therefore the aim of this pilot study was to evaluate its suitability.

In the second part of the experiment you were asked to either choose the correct fragment of shape sequences (inclusion instructions) or to avoid choosing the correct fragment of shape sequences (exclusion instructions). Under inclusion instructions your performance could be influenced by both implicit and explicit knowledge while exclusion performance requires explicit knowledge: you need to be conscious of knowing parts of the sequence to the able to avoid generating them.

We aim to evaluate whether PDP can discriminate between explicit and implicit knowledge when used with sequences of shapes. The result of this experiment will be of crucial importance for the planning of future investigations of explicit and implicit knowledge in sequential regularities learning.

This study is part of a PhD project conducted by Federica Menchinelli (fmenchinelli@lincoln.ac.uk) under the supervision of Dr Simon Durrant and Dr Petra Pollux.

For further questions contact: Federica Menchinelli (fmenchinelli@lincoln.ac.uk).

Appendix C: Standardised verbal instructions

In addition to on-screen instructions, before both inclusion and exclusion conditions, the experimenter provided further verbal instructions to ensure that participants understood what was required of them, and the meaning of the confidence ratings and knowledge attribution ratings. Consistency between participants was maintained by ensuring that the below was repeated verbatim for each participant. The wording of instructions changed slightly depending on whether the experiment was in the visual or auditory modality.

Two-alternative forced-choice task instructions (for the inclusion condition)

> "You will see two sequences of shapes: you will see a sequence, then a break, then another sequence, and then you will be asked to choose which of the two sequences looks/ sounds to you more familiar[8], based on what you watched/ heard at the beginning. You will be asked to press one (*experimenter indicates key on keyboard*) if the first sequence you saw/ heard is more familiar[9] or two (*experimenter indicates key on keyboard*) if the second sequence you saw/heard is more familiar…"

Two-alternative forced-choice task instructions (for the exclusion condition)

> "You will see two sequences of shapes: you will see a sequence, then a break, then another sequence, and then you will be asked to choose which of the two sequences looks/ sounds to you less familiar, based on what you watched/ heard at the beginning. You will be asked to press one

---

[8] The wording "which of the two sequences looks/ sounds to you more familiar" was utilised from Chapter 3 of this thesis onwards. Chapter 2 utilised the wording "which of the two sequences is correct", for inclusion and "which of the two sequences is incorrect" for exclusion instead. This applied to both the visual and auditory experiment.

[9] The wording "is more familiar" was utilised from Chapter 3 of this thesis. Chapter 2 utilised the wording "is correct" for inclusion, and "is incorrect" for exclusion.

(*experimenter indicates key on keyboard*) if the first sequence you saw/ heard is less familiar or two (*experimenter indicates key on keyboard*) if the second sequence you saw/heard is less familiar…"

Confidence ratings instructions

"….Then, you will be asked to enter any number between 50 and 100 to indicate how confident you are in your choice. Fifty is a guess, you may as well have flipped a coin, and 100 is complete certainty that your choice was correct…"

Knowledge attribution ratings instructions (wording adapted from Dienes & Scott, 2005).

"…After, you will be asked to indicate what type of knowledge you used to make your choice. You will be asked to choose between guess, intuition, memory or rules. Guess is if your judgment has no basis whatsoever, you could just as well have flipped a coin to arrive at that judgment. Intuition is if you have at least some confidence in your judgment. You know to some degree that your judgment is right but you have no idea why it is right. Memory is if you feel that your judgment is based on memory for a particular item or parts of items from the exposure phase. Rules[10] is if you feel that your answer is based on some rule or rules acquired from the training phase, and which you could state, if asked…"

---

[10] The Rules knowledge attribution was only used in Chapter 2 of this thesis, and removed thereafter.

Four-alternative forced-choice task (4AFCT) instructions

These instructions were used in Chapter 4 of this thesis to replace the 2AFC task instructions in the 4AFC phase of our visual experiments. They were followed by the confidence ratings instructions and knowledge attribution ratings instructions.

> "You will be shown a sequence of shapes, but one shape will be missing from the sequence. The missing shape will be indicated by a question mark. You will then be asked which of four shapes you think fits in place of the question mark. Press keys 1 to 4 to make your response…"

Generation task instructions

These instructions were used in Chapter 4 of this thesis.

> "These are the twelve shapes you saw in this experiment. The shapes always appeared in groups of three. In this experiment there were four different groups of three shapes each. Fill this table by dragging and dropping each shape into one of the boxes to form as many of the four groups of three shapes as you can remember"

Appendix D: Chapter 3 additional information

D.1 Auditory triplet learning: participant information sheet, consent form and debrief

A pilot investigation into the mechanisms of auditory sequence processing.

Information sheet

Thank you for your interest in this study.

We aim to investigate the processing of auditory stimuli in a computer- based experiment which will consist of two parts. In the first part you will be asked to simply listen to a series of tones played through headphones. In the second part you will be asked to listen to the tones again and will be asked some simple questions about them.

The experiment should take no longer than 30 minutes overall and you will be granted 2 credit points for your participation.

All the information collected about you for the purpose of this study will be anonymised and kept confidential. Please remember that you have the right to withdraw your data from the study at a later stage, should you wish to do so. Please remember that you have the right to withdraw from this study at any point without providing any motivation.

This study is part of a PhD project conducted by Federica Menchinelli (fmenchinelli@lincoln.ac.uk) under the supervision of Dr Simon Durrant (sidurrant@lincoln.ac.uk) and Dr Petra Pollux (ppollux@lincoln.ac.uk).

The study has received ethical clearance by the School of Psychology Research Ethics Committee (University of Lincoln). If you have any queries about the research ethics, please contact SOPREC (School of Psychology Research Ethics) soprec@lincoln.ac.uk.

A pilot investigation into the mechanisms of auditory sequence processing.

Consent Form

Please indicate whether you consent to taking part in this study by answering the questions below:

- I have read and understood the participant information sheet **Yes/ No**
- I confirm that I am eligible to take part in this study **Yes/ No**
- I have had the opportunity to ask any questions **Yes/ No**
- My questions have been answered satisfactorily **Yes/ No**
- I understand that:

  I am free to withdraw from the study at any time and without having to provide a reason **Yes/ No**

  All the information collected about me will be anonymised and kept confidential **Yes/ No**

- I agree to take part in this study **Yes/ No**

I agree to take part in this computer-based study. This will involve listening to a series of tones and answering some questions. I will be granted 2 credit points for my participation.

Signed (participant) ______________________________

Signed (researcher) ______________________________

Date ________________

This study is part of a PhD project conducted by Federica Menchinelli (fmenchinelli@lincoln.ac.uk) under the supervision of Dr Simon Durrant (sidurrant@lincoln.ac.uk) and Dr Petra Pollux (ppollux@lincoln.ac.uk).

The study has received ethical clearance by the School of Psychology Research Ethics Committee (University of Lincoln). If you have any queries about the research ethics, please contact SOPREC (School of Psychology Research Ethics) soprec@lincoln.ac.uk.

A pilot investigation into the mechanisms of auditory sequence processing.

Participant Debrief

Thank you for your participation.

This experiment has tested your learning of auditory sequences with a regular structure (sequential regularities learning). Our aim is to understand the roles of implicit (unconscious) and explicit (conscious) knowledge in this type of learning.

To distinguish your implicit and explicit knowledge of the sound sequence, we have used a well- established test called the Process Dissociation Procedure (PDP). This test has never been previously used with this type of stimuli, therefore the aim of this pilot study was to evaluate its suitability.

In the second part of the experiment you were asked to either choose the sequence that sounded more familiar (inclusion instructions) or to choose the sequence that sounded less familiar (exclusion instructions). Under inclusion instructions your performance could be influenced by both implicit and explicit knowledge while exclusion performance requires explicit knowledge: you need to be conscious of knowing parts of the sequence to the able to avoid choosing them. We aim to evaluate whether PDP can discriminate between explicit and implicit knowledge when used with this type of stimuli.

The result of this experiment will be of crucial importance for the planning of future investigations of explicit and implicit knowledge in sequential regularities learning.

This study is part of a PhD project conducted by Federica Menchinelli (fmenchinelli@lincoln.ac.uk) under the supervision of Dr Simon Durrant and Dr Petra Pollux.

For further questions contact: Federica Menchinelli (fmenchinelli@lincoln.ac.uk).

D.2 Visual triplet learning: participant information sheet, consent form and debrief

A pilot investigation into the mechanisms of visual sequence processing.

Information sheet

Thank you for your interest in this study.

We aim to investigate the processing of visual stimuli in a computer- based experiment which will consist of two parts. In the first part you will be asked to simply watch a series of shapes presented in the centre of the screen. In the second part you will be asked to watch the shapes again and will be asked some simple questions about them.

The experiment should take no longer than 30 minutes overall and you will be granted 2 credit points for your participation.

All the information collected about you for the purpose of this study will be anonymised and kept confidential. Please remember that you have the right to withdraw your data from the study at a later stage, should you wish to do so. Please remember that you have the right to withdraw from this study at any point without providing any motivation.

This study is part of a PhD project conducted by Federica Menchinelli (fmenchinelli@lincoln.ac.uk) under the supervision of Dr Simon Durrant (sidurrant@lincoln.ac.uk) and Dr Petra Pollux (ppollux@lincoln.ac.uk).

The study has received ethical clearance by the School of Psychology Research Ethics Committee (University of Lincoln). If you have any queries about the research ethics, please contact SOPREC (School of Psychology Research Ethics) soprec@lincoln.ac.uk.

A pilot investigation into the mechanisms of visual sequence processing.

Consent Form

Please indicate whether you consent to taking part in this study by answering the questions below:

- I have read and understood the participant information sheet **Yes/ No**
- I confirm that I am eligible to take part in this study **Yes/ No**
- I have had the opportunity to ask any questions **Yes/ No**
- My questions have been answered satisfactorily **Yes/ No**
- I understand that:

    I am free to withdraw from the study at any time and without having to provide a reason **Yes/ No**

    All the information collected about me will be anonymised and kept confidential **Yes/ No**

- I agree to take part in this study **Yes/ No**

I agree to take part in this computer-based study. This will involve watching a series of shapes and answering some questions. I will be granted 2 credit points for my participation.

Signed (participant) ______________________________

Signed (researcher) ______________________________

Date ________________

This study is part of a PhD project conducted by Federica Menchinelli (fmenchinelli@lincoln.ac.uk) under the supervision of Dr Simon Durrant (sidurrant@lincoln.ac.uk) and Dr Petra Pollux (ppollux@lincoln.ac.uk).

The study has received ethical clearance by the School of Psychology Research Ethics Committee (University of Lincoln). If you have any queries about the research ethics, please contact SOPREC (School of Psychology Research Ethics) soprec@lincoln.ac.uk.

A pilot investigation into the mechanisms of visual sequence processing.

Participant Debrief

Thank you for your participation.

This experiment has tested your learning of visual sequences with a regular structure (sequential regularities learning). Our aim is to understand the roles of implicit (unconscious) and explicit (conscious) knowledge in this type of learning.

To distinguish your implicit and explicit knowledge of the shape sequence we have used a well- established test called the Process Dissociation Procedure (PDP). This test has never been previously used with this type of stimuli, therefore the aim of this pilot study was to evaluate its suitability.

In the second part of the experiment you were asked to either choose the shape sequence that looked more familiar (inclusion instructions) or to choose the shape sequence that looked less familiar (exclusion instructions). Under inclusion instructions your performance could be influenced by both implicit and explicit knowledge while exclusion performance requires explicit knowledge: you need to be conscious of knowing parts of the sequence to the able to avoid choosing them. We aim to evaluate whether PDP can discriminate between explicit and implicit knowledge when used with this type of stimuli.

The result of this experiment will be of crucial importance for the planning of future investigations of explicit and implicit knowledge in sequential regularities learning.

This study is part of a PhD project conducted by Federica Menchinelli (fmenchinelli@lincoln.ac.uk) under the supervision of Dr Simon Durrant and Dr Petra Pollux.

For further questions contact: Federica Menchinelli (fmenchinelli@lincoln.ac.uk).

Appendix E: Chapter 4 additional information

E.1 Direct and indirect measures in adults – Version 1: participant information sheet, consent form and debrief[11]

[11] Note that the second-year student Aisling E. Treacy supported the researcher with data collection for half of the sample for Chapter 4 of this thesis, as part of her research internship elective. This is reflected in the "further information" section of the debrief form.

A pilot investigation into the mechanisms of visual sequence processing.

Information sheet

Thank you for your interest in this study.

We aim to investigate the processing of visual stimuli in a computer- based experiment which will consist of two parts. In the first part you will be asked to simply watch a series of shapes presented in the centre of the screen. In the second part you will be asked to watch the shapes again and will be asked some simple questions about them.

The experiment should take no longer than 45 minutes overall and you will be granted 3 credit points for your participation.

All the information collected about you for the purpose of this study will be anonymised and kept confidential. Please remember that you have the right to withdraw your data from the study at a later stage, should you wish to do so. Please remember that you have the right to withdraw from this study at any point without providing any motivation.

This study is part of a PhD project conducted by Federica Menchinelli (fmenchinelli@lincoln.ac.uk) under the supervision of Dr Simon Durrant (sidurrant@lincoln.ac.uk) and Dr Petra Pollux (ppollux@lincoln.ac.uk).

The study has received ethical clearance by the School of Psychology Research Ethics Committee (University of Lincoln). If you have any queries about the research ethics, please contact SOPREC (School of Psychology Research Ethics) soprec@lincoln.ac.uk.

A pilot investigation into the mechanisms of visual sequence processing.

Consent Form

Please indicate whether you consent to taking part in this study by answering the questions below:

- I have read and understood the participant information sheet **Yes/ No**
- I confirm that I am eligible to take part in this study **Yes/ No**
- I have had the opportunity to ask any questions **Yes/ No**
- My questions have been answered satisfactorily **Yes/ No**
- I understand that:

  I am free to withdraw from the study at any time and without having to provide a reason **Yes/ No**

  All the information collected about me will be anonymised and kept confidential **Yes/ No**

- I agree to take part in this study **Yes/ No**

I agree to take part in this computer-based study. This will involve watching a series of shapes and answering some questions. I will be granted 3 credit points for my participation.

Signed (participant) ______________________________

Signed (researcher) ______________________________

Date ________________

This study is part of a PhD project conducted by Federica Menchinelli (fmenchinelli@lincoln.ac.uk) under the supervision of Dr Simon Durrant (sidurrant@lincoln.ac.uk) and Dr Petra Pollux (ppollux@lincoln.ac.uk).

The study has received ethical clearance by the School of Psychology Research Ethics Committee (University of Lincoln). If you have any queries about the research ethics, please contact SOPREC (School of Psychology Research Ethics) soprec@lincoln.ac.uk.

The processing of visual sequences

Participant debrief

Thank you for your participation.

This experiment has tested your learning of visual sequences with a regular structure (visual statistical learning).

We have made use of a well-known visual triplet learning paradigm (Turk-Browne et al, 2005) consisting of presentation of a stream of abstract shapes which are, unbeknownst to the participant, concatenated to form groups of three shapes (triplets). Both children and adults have shown an ability to learn this triplet structure and therefore are able to discriminate learned triplets from previously unseen triplets in a subsequent forced-choice test. However, we still do not know if the knowledge acquired in this task is conscious or unconscious.

You first completed a learning phase, in which you were given a distractor task (detecting a cartoon character) to ensure continued attention to the visual stimuli. After this, your knowledge of the triplet structure was assessed through a two-alternative forced-choice task, where you had to choose between a previously seen triplet and a new triplet and a four-alternative forced-choice task, where you had to identify which of four shapes was missing from a triplet. You were also asked to indicate your level of confidence and if you were guessing, remembering or using your intuition. Good performance on trials when you felt that you were guessing is an indication of unconscious knowledge. We will also compare your level of confidence for correct and incorrect responses.

After this, a speeded detection task was used as an indirect assessment of knowledge through comparison of response times to the first, second and third shape of a triplet: if the triplets have been learned, response times to the third shape within a triplet should be faster than to the second or third shape in a triplet, because more predictable.

Lastly, your explicit memory of the triplet structure was assessed through a generation task: you were asked to try to reproduce the shape triplets that you could remember.

The data collected will be very useful in comparing the efficacy of direct and indirect measures of knowledge in statistical learning.

Thank you for your time!

This study is part of a PhD project conducted by Federica Menchinelli (fmenchinelli@lincoln.ac.uk) under the supervision of Dr Simon Durrant and Dr Petra Pollux. The researcher is Aisling E. Treacy (15593746@students.lincoln.ac.uk). For further questions contact: Federica Menchinelli (fmenchinelli@lincoln.ac.uk).

E.2 Direct and indirect measures in adults – Version 2: participant information sheet, consent form and debrief[12]

A pilot investigation into the mechanisms of visual sequence processing.

Information sheet

Thank you for your interest in this study.

We aim to investigate the processing of visual stimuli in a computer- based experiment which will consist of two parts. In the first part you will be asked to simply watch a series of shapes presented in the centre of the screen. In the second part you will be asked to watch the shapes again and will be asked some simple questions about them.

The experiment should take no longer than 45 minutes overall and you will be granted 3 credit points for your participation.

All the information collected about you for the purpose of this study will be anonymised and kept confidential. Please remember that you have the right to withdraw your data from the study at a later stage, should you wish to do so. Please remember that you have the right to withdraw from this study at any point without providing any motivation.

This study is part of a PhD project conducted by Federica Menchinelli (fmenchinelli@lincoln.ac.uk) under the supervision of Dr Simon Durrant (sidurrant@lincoln.ac.uk) and Dr Petra Pollux (ppollux@lincoln.ac.uk).

[12] Note that the second-year student Aisling E. Treacy supported the researcher with data collection for half of the sample for Chapter 4 of this thesis, as part of her research internship elective. This is reflected in the “further information” section of the debrief form.

The study has received ethical clearance by the School of Psychology Research Ethics Committee (University of Lincoln). If you have any queries about the research ethics, please contact SOPREC (School of Psychology Research Ethics) soprec@lincoln.ac.uk.

A pilot investigation into the mechanisms of visual sequence processing.

Consent Form

Please indicate whether you consent to taking part in this study by answering the questions below:

- I have read and understood the participant information sheet **Yes/ No**
- I confirm that I am eligible to take part in this study **Yes/ No**
- I have had the opportunity to ask any questions **Yes/ No**
- My questions have been answered satisfactorily **Yes/ No**
- I understand that:

  I am free to withdraw from the study at any time and without having to provide a reason **Yes/ No**

  All the information collected about me will be anonymised and kept confidential **Yes/ No**

- I agree to take part in this study **Yes/ No**

I agree to take part in this computer-based study. This will involve watching a series of shapes and answering some questions. I will be granted 3 credit points for my participation.

Signed (participant) ______________________________

Signed (researcher) ______________________________

Date ________________

This study is part of a PhD project conducted by Federica Menchinelli (fmenchinelli@lincoln.ac.uk) under the supervision of Dr Simon Durrant (sidurrant@lincoln.ac.uk) and Dr Petra Pollux (ppollux@lincoln.ac.uk).

The study has received ethical clearance by the School of Psychology Research Ethics Committee (University of Lincoln). If you have any queries about the research ethics, please contact SOPREC (School of Psychology Research Ethics) soprec@lincoln.ac.uk.

The processing of visual sequences

Participant debrief

Thank you for your participation.

This experiment has tested your learning of visual sequences with a regular structure (visual statistical learning).

We have made use of a well-known visual triplet learning paradigm (Turk-Browne et al, 2005) consisting of presentation of a stream of abstract shapes which are, unbeknownst to the participant, concatenated to form groups of three shapes (triplets). Both children and adults have shown an ability to learn this triplet structure and therefore are able to discriminate learned triplets from previously unseen triplets in a subsequent forced-choice test. However, we still do not know if the knowledge acquired in this task is conscious or unconscious.

You first completed a learning phase, in which you were familiarised with the visual stimuli. After this, your knowledge of the triplet structure was assessed through a two-alternative forced-choice task, where you had to choose between a previously seen triplet and a new triplet and a four-alternative forced-choice task, where you had to identify which of four shapes was missing from a triplet. You were also asked to indicate your level of confidence and if you were guessing, remembering or using your intuition. Good performance on trials when you felt that you were guessing is an indication of unconscious knowledge. We will also compare your level of confidence for correct and incorrect responses.

After this, a speeded detection task was used as an indirect assessment of knowledge through comparison of response times to the first, second and third shape of a triplet: if the triplets have been learned, response times to the third shape within a triplet should be faster than to the second or third shape in a triplet, because more predictable.

Lastly, your explicit memory of the triplet structure was assessed through a generation task: you were asked to try to reproduce the shape triplets that you could remember.

The data collected will be very useful in comparing the efficacy of direct and indirect measures of knowledge in statistical learning.

Thank you for your time!

This study is part of a PhD project conducted by Federica Menchinelli (fmenchinelli@lincoln.ac.uk) under the supervision of Dr Simon Durrant and Dr Petra Pollux. The researcher is Aisling E. Treacy (15593746@students.lincoln.ac.uk). For further questions contact: Federica Menchinelli (fmenchinelli@lincoln.ac.uk).

E.3 On-screen task instructions

Direct and indirect measures in adults – Version 1: on-screen task instructions for the exposure phase

You will see a series of shapes. Your task is to watch these shapes, but be careful because sometimes Homer will suddenly pop up on the screen. Press the space bar as soon as you see Homer to catch him before he disappears. READY?

Direct and indirect measures in adults – Version 2: on-screen task instructions for the exposure phase

You will see a series of shapes. Please watch attentively.

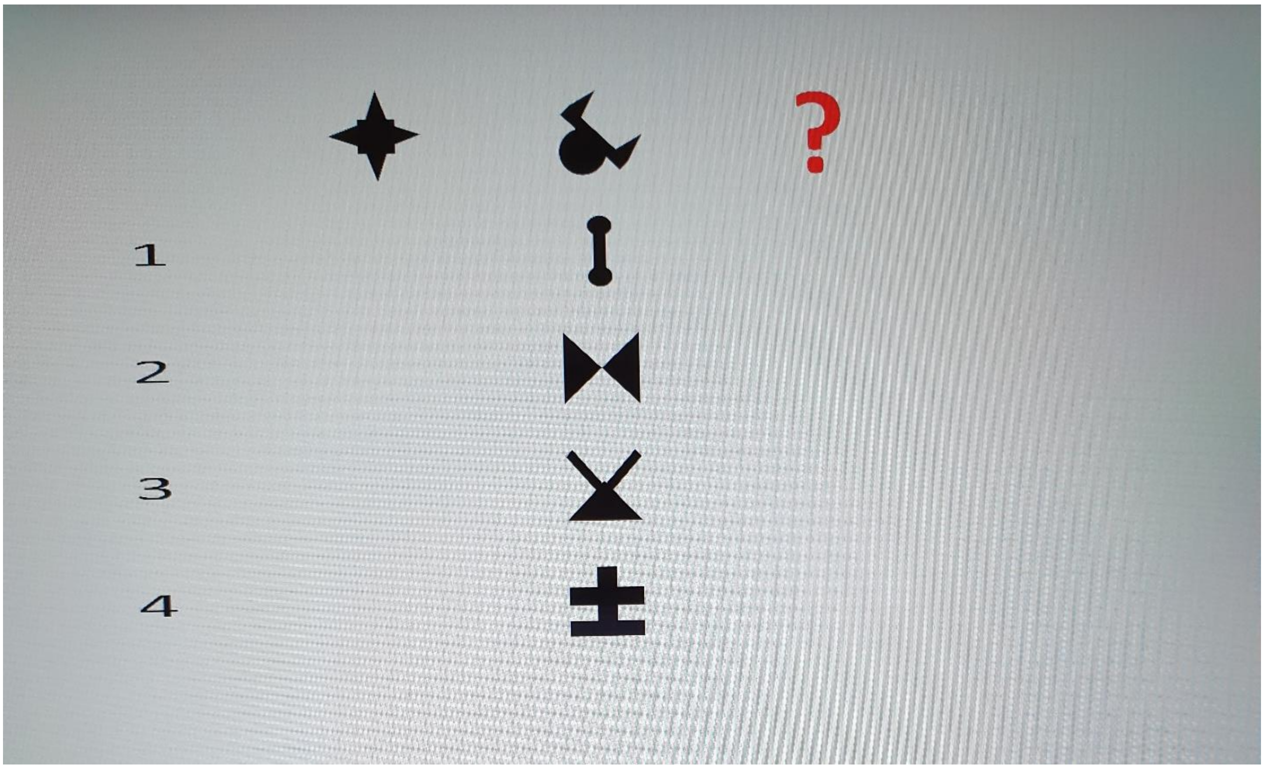
Direct and indirect measures in adults – Version 1 and Version 2: on-screen task instructions for the RSVP task[13]

Sequences of shapes will be presented rapidly on the screen. Before each sequence you will see a shape target. Press the space bar as soon as you see the target within each sequence. Respond as quickly and accurately as possible. Press enter to start.

[13] The same instructions were given before the practice trial and before the "real" experiment. Before the practice trial, participants were alerted by the experimenter that what was coming up was only a practice run.

E.4 Visual display of the 4AFC task

Static visual display for the 4AFC task



N.B. The visual shapes were black and presented on a white background. Colours may be slightly altered in this photograph of the visual display.

E.5 Direct and indirect measures in children – additional information

E.5.1 Summer Scientist Week ethics application and study information forms

Summer Scientist Week Experiment Information

Please complete the two following forms.

Form 1 will provide us with all the information we need to organise and advertise the summer scientist week. It also includes a declaration for you to sign.

Form 2 will provide us with all the information we need to get ethical approval. All studies that will run during the summer scientist week will be submitted into a single and joined ethical application.

<u>FORM 1: practical information</u>

1. Name of the person who will be collecting the data	Federica Menchinelli
2. Supervisor (if relevant)	Simon Durrant, Petra Pollux
3. Study title (in scientific terms) Implicit and explicit processes in children's visual statistical learning.	

<table>
<tr><td>4. Age range of participants (between 3 - 10 years)</td><td>9-10 years</td></tr>
<tr><td>5. Number of participants tested at a time</td><td>20</td></tr>
<tr><td>6. How long will your study take to run with each participant?</td><td>15 minutes</td></tr>
<tr><td colspan="2">7. Please give brief details of the type of activities your study (e.g. making decisions about stimuli presented on a computer).

There will be four types of activities involved in the study
4) Watching a series of abstract shapes on a computer screen whilst detecting the presence of a cartoon character appearing at random points within the stream.
5) Completing a two-alternative-forced-choice task testing discrimination of previously seen groups of shapes from unseen groups.
6) On each trial of the forced-choice task, providing a confidence rating on a binary scale (“know”/ “guess”)
7) Completing a computer-based speeded detection task, which will record response times to a target shape embedded within a fast stream of shapes.</td></tr>
<tr><td colspan="2">8. How much space do you need to run the study?

A very small room would be sufficient. No special equipment is needed other than a computer.</td></tr>
<tr><td colspan="2">9. Does the study involve any noisy activities (e.g. running, playing sounds etc.) that would disturb other studies happening in the same room?

No, the study does not involve sound. All noise will be limited to conversation between the researcher and the participant. It will be necessary for participants to concentrate, as these tasks</td></tr>
</table>

will measure learning and response times, therefore any excessively noisy activities taking place in the same room might be disruptive for this experiment.

10. Are there any activities that might provide specific Health & Safety concerns?

No

11. What furniture do you need (e.g. one child-sized table and two child-sized chairs plus a larger chair for an accompanying parent)?

The experiment will run on a laptop. A table and chair will be needed for children to sit comfortably at the laptop, plus one extra chair for an accompanying parent.

12. What equipment do you need (including sockets)? Please clearly indicate what equipment you will provide and what you expect us to provide. Please note that we cannot provide you with specialist equipment.

We will provide a laptop to run the experiment. In the testing room there will need to be one plug socket for the laptop, as well as basic furniture (a table and a chair for the participant to sit).

13. What participant restrictions do you have (e.g. gender restrictions, can you test children with special education needs or developmental disorders)?

We are looking for both males and females aged 8-10 years. We would like to exclude children with special education needs or any developmental disorders which might affect their learning abilities.

14. Does the study involve any questionnaires to be completed by the parent? If yes, please describe.

There will be a very brief questionnaire to be completed by parents. This will contain a few very simple questions relating to their child's musical abilities and musical training.

15. Do you have any publications relevant to this project? If yes, please name them.

I have not published any papers relevant to this project.

16. Does the person testing already have DBS clearance from the University? **If not, please provide their email address**	No, a DBS application will need to be made. My email address is fmenchinelli@lincoln.ac.uk

17. Your study will need to be presented in lay terms in the consent form and advertisement materials. See last year's consent form here attached for some examples. Based on those examples:

Please provide a funny title for your study which should be framed as a "game":

Catch the shape!

Please provide a brief description of your study suitable for parents (around 100 words). Avoid words like experiment, stimuli, and any specialist terms.

We are interested in children's ability to learn specific sequences of shapes. Your child will be asked to play a game involving familiarisation with, and recognition of, different shapes.

We will first play a video showing a long sequence of shapes. Occasionally, a cartoon character will appear on the screen and your child will be asked to "catch" it as quickly as possible by pressing a key. This is so that your child can become familiar with the sequence of shapes. After this, we will play a memory game where your child will be asked which of two groups of shapes looks familiar to him/her, and how confident they are in their responses. Finally, we will play a "shape detection" game: we will show your child a fast stream of shapes and ask him/her to press a key as quickly as possible to "catch" a shape target. Overall, the session will take no longer than 15 minutes.

The results of these tasks will help us understand more about how children's learning and memory work. Thank you for your help!

I confirm that by registering for the Summer Scientist Week 2017 I am giving full commitment to the dates 21st - 25th August 2017 inclusive. **Despite any changes to my project before and/or during the event I will be available and committed to contributing to the event.** **Activities may include planning and promoting the event, providing games/activities with the participants, writing a post-event report for the Newsletter.**

Signature:	Federica Menchinelli	Date:	22/05/2017

FORM 2: ethical application

Please read carefully the following notes:

The information provided on this form will form the basis of a joint ethics application submitted for all studies running as part of the Summer Scientist Week. Please fill out all sections of the form, even if you have already received ethical clearance for your study.

There is no need to provide your own information sheet and consent form. Parents will receive a single information sheet with details of all studies (see last year's example) and one consent form. This will allow them to opt out of particular studies if desired.

All children will be presented with a gift pack before they leave including a certificate, pencil and t-shirt/baseball cap, therefore it is not necessary to provide rewards for individual studies.

IMPORTANTLY, it will not be possible to amend the ethics application once it has been submitted, therefore if possible please ensure that the information you provide will cover any small changes (not affecting the ethical concerns) that may need to be made at a later date.

Has this study received ethical clearance (please tick all that apply):

f) **yes, from SOPREC for the use with children of this age group ___**

g) **yes, as part of previous SSW events in Lincoln ___**

h) **yes, from SOPREC for the use with students _X__**

i) **yes, from SOPREC for the use with other groups ___**

j) **yes, from elsewhere (please briefly specify) ___**

Do you need to run any standardised tests with your study, e.g. language development?

b) **yes ___**
Please state which tests and whether you will run them

b) no _X__

Study Description – Rationale

Statistical learning is our ability to extract underlying regularities from statistically structured stimuli. This project aims to understand the extent to which implicit and explicit knowledge are acquired as a result of statistical learning in children. The data collected will be compared to adult data with the aim to assess the extent to which direct and indirect measures of knowledge are suitable in children, as well as compare the use of implicit and explicit knowledge in statistical learning between age groups.

Procedure

We will make use of a well-known visual triplet learning paradigm (Turk-Browne et al, 2005) consisting of presentation of a stream of abstract shapes which are, unknown to the participant, concatenated to form groups of three shapes (triplets). Both children (Arciuli & Simpson, 2012; Bertels et al, 2015) and adults (Fiser & Aslin, 2002) have shown an ability to learn this triplet structure and therefore are able to discriminate learned triplets from previously unseen triplets in a subsequent forced-choice test. Our tasks will replicate the methodology used by Bertels et al (2015). The first phase of our experiment (familiarisation) will involve children viewing a stream of shapes presented on a monitor for approximately four minutes. To ensure continued attention, children will be given a cover task involving detection of a cartoon character which will appear at random points in the exposure stream. This will be followed by an objective assessment of learning of the triplet structure through a four-alternative forced-choice task: children will be presented with an incomplete triplet and will be asked to choose, amongst four shapes, which one correctly completes the triplet. Binary confidence judgments (guess/ remember) will be collected on a trial-by-trial basis for a subjective assessment of confidence. After this, a speeded detection task will be used as an indirect assessment of triplet knowledge through comparison of response times to the first, second and third shape in a triplet. This task will involve children viewing several streams of shapes and making a speeded response to a specific shape target. The experiment will take approximately 15 minutes to complete.

Age of participants **(note:** It will only be possible to test the age groups you have ethical permission for, therefore please include any age groups you may be likely to test as it will not be possible to amend the ethics application at a later date.)

8-10 years

Please provide in appendix any written experimental materials if relevant (e.g. questionnaires).

Please see Appendix A

Specific Ethical Concerns

You do not need to explain participants tested outside the school, participants under or participants recruited from special sources as these apply to all studies and will be covered in the general application.

There are no specific ethical concerns associated to this project. The on-screen stimuli used will be simple abstract shapes and a picture of a cartoon character, as used in a previous study on statistical learning in children. The duration of individual tasks will not be excessive: five minutes for the exposure (cartoon character detection) phase and 10 minutes for the two remaining tasks (two-alternative forced-choice and speeded detection task). Participants will be free to leave the study at any time, should they wish to do so.

Appendix A

Questionnaire for parents: what is your child's level of musical training?

(Please note: all responses will be provided on an agreement scale 1-7)

1. Your child has been complimented for his/her talents as a musical performer.
2. Your child has engaged in regular, daily practice of a musical instrument for how many years?
3. At the peak of his/her interest, how many hours per day did/does your child practice on his/ her primary instrument?
4. Your child has had formal training in music theory for how many years?
5. How many years of formal training on a musical instrument (including voice) has your child had?
6. How many musical instruments can your child play?

DOB

Age

Pp code

School performance:

What academic year has your child just completed?

E.5.2 Additional information for parents

Catch the shape - Further information for parents

Implicit and explicit processes in children's visual statistical learning.

Statistical learning is our ability to extract underlying regularities from statistically structured stimuli. This project aims to understand the extent to which implicit (unconscious) and explicit (conscious) knowledge are acquired as a result of statistical learning in children.

We are making use of a well-known visual triplet learning paradigm (Turk-Browne et al, 2005) consisting of presentation of a stream of abstract shapes which are, unknown to the participant, concatenated to form groups of three shapes (triplets). Both children and adults have shown an ability to learn this triplet structure and therefore are able to discriminate learned triplets from previously unseen triplets in a subsequent forced-choice test. However, we still do not know if the knowledge acquired in this task is conscious or unconscious and whether children and adults differ in the type of knowledge they acquire.

The first phase of the experiment aims to familiarise children with the stream of shapes. The four-alternative forced-choice task after this is to assess learning of the triplet structure. Both conscious and unconscious knowledge could contribute to performance in this task. Children are also asked if they are guessing or remembering: good performance on trials when children are claiming to be guessing is taken as an indication of unconscious knowledge. After this, a speeded detection task is used as an indirect assessment of knowledge through comparison of response times to the first, second and third shape of a triplet: if the triplets have been learned, response times to the third shape within a triplet should be faster than to the second or third shape in a triplet, because more predictable.

The data collected will be compared to adult data with the aim to assess the extent to which direct and indirect measures of knowledge are suitable in children, as well as compare the use of implicit and explicit knowledge in statistical learning between age groups.

Statement of ethical approval

All the information collected about your child for the purpose of this study will be anonymised and kept confidential. Please remember that you have the right to withdraw your child's data from the study at a later stage, should you wish to do so. Your child can withdraw from the study at any point if he/ she wishes.

This study has received ethical clearance by the School of Psychology Research Ethics Committee (University of Lincoln). If you have any queries about the research ethics, please let the researcher know.

Catch the shape

What does this game involve?

We are interested in children's ability to learn specific sequences of shapes. Your child will be asked to play a game involving familiarisation with, and recognition of, different shapes.

We will first play a video showing a long sequence of shapes. Occasionally, a cartoon character will appear on the screen and your child will be asked to "catch" it as quickly as possible by pressing a key. This is so that your child can become familiar with the sequence of shapes. After this, we will play a memory game where your child will be asked which of two groups of shapes looks familiar to him/her, and how confident they are in their responses. Finally, we will play a "shape detection" game: we will show your child a fast stream of shapes and ask him/her to press a key as quickly as possible to "catch" a shape target. Overall, the session will take no longer than 15 minutes.

The results of these tasks will help us understand more about how children's learning and memory work. Thank you for your help!

E.5.3 Catch the shape: full task instructions

Instructions were displayed on the computer screen as part of the experiment and read out loud by the experimenter. Any other clarifications were given verbally, if needed. Before starting the experiment, all participants were informed of the structure of the game by the experimenter saying: “This game will be in three parts”.

Exposure instructions

I will play a short film showing you a sequence of different shapes. Your task is to watch these shapes. But be careful, because sometimes Homer will suddenly pop up on the screen *(show Homer on the screen).* Press the space bar as soon as you see Homer to catch him before he disappears!

4AFC task instructions

I will tell you a secret about the film you just watched: the shapes you saw always followed each other in groups of three. In this game you will see a group of three shapes that has appeared before in the video but one shape will be missing!

I will give you four shapes to choose from: which one do you think fits in the group?

The following instruction was provided verbally by the experimenter. Consistency was ensured by repeating the instructions verbatim for each participant:

> “You will need to choose whether you were guessing or remembering. Guess is if you had no idea, you answered at random.

Remember is if you remember this group of shapes from the film at the beginning”

RSVP task initial instructions

This game is about catching a shape before it disappears. First, there will be a target shape in the centre of the screen. This is the shape you need to catch. Then, there will be a fast sequence of shapes. Press the space bar as quickly as possible when you see the target shape before it disappears! Ready?

RSVP pre-practice instructions

This is just for practice

RSVP post-practice instructions

Are you ready for the real thing?

E.5.4 Questionnaire for parents

Questionnaire for parents

SECTION 1

General information

What is your child's age? ________________________

What academic year has your child just completed? ___________________

SECTION 2

We are interested in your child's musical abilities because these have been found to correlate with the ability to learn the structure of visual and auditory stimuli.

Below are a few quick questions on your child's level of musical training. Please circle to indicate your chosen answer:

- Your child has been complimented for his/her talents as a musical performer.

1 Completely Disagree	2 Strongly Disagree	3 Disagree	4 Neither Agree nor Disagree	5 Agree	6 Strongly Agree	7 Completely Agree
1	2	3	4	5	6	7

- Your child has engaged in regular, daily practice of a musical instrument for how many years?

0 / 1 / 2 / 3 / 4-5 / 6-9 / 10 or more years.

- At the peak of his/her interest, how many hours per day did/does your child practice on his/ her primary instrument?

  0 / 0.5 / 1 / 1.5 / 2 / 3-4 / 5 or more hours

- Your child has had formal training in music theory for how many years?

  0 / 0.5 / 1 / 2 / 3 / 4-6 / 7 or more years.

- How many years of formal training on a musical instrument (including voice) has your child had?

  0 / 0.5 / 1 / 2 / 3-5 / 6-9 / 10 or more years

- How many musical instruments can your child play?

  0 / 1 / 2 / 3 / 4 / 5 / 6 or more musical instruments.

SECTION 3

The ability to understand the structure of sequences of stimuli could relate to several other abilities. We are interested in finding out more and, for this reason, we would like to ask you some questions about your child's preference for certain school subjects and their performance in those subjects.

Please indicate your response to the questions below. Feel free to skip any questions that you do not wish to answer:

On a scale from 1 to 10, how would you rate your child's performance, compared to other children in his/ her class, on the following subjects?

Mathematics 1 2 3 4 5 6 7 8 9 10

English 1 2 3 4 5 6 7 8 9 10

Science 1 2 3 4 5 6 7 8 9 10

Foreign languages (if applicable) 1 2 3 4 5 6 7 8 9 10

Art (if applicable) 1 2 3 4 5 6 7 8 9 10

How would you rate your child's enjoyment of the following subjects?

Mathematics 1 2 3 4 5 6 7 8 9 10

English 1 2 3 4 5 6 7 8 9 10

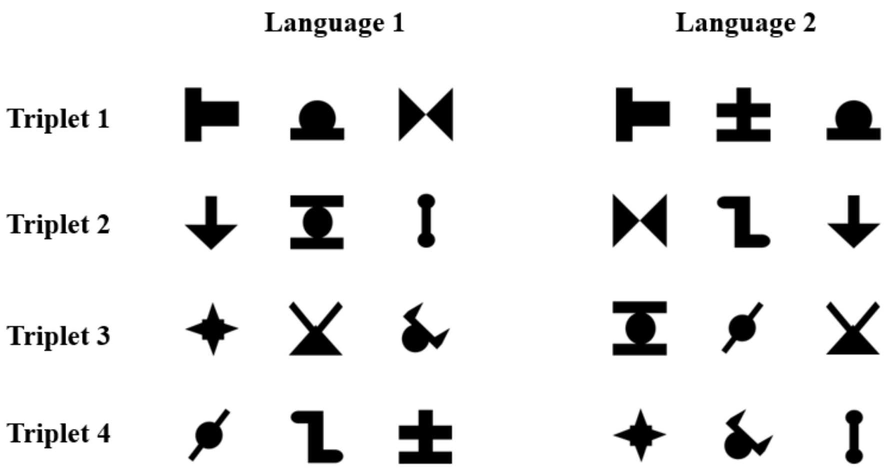
Science 1 2 3 4 5 6 7 8 9 10

Foreign languages (if applicable) 1 2 3 4 5 6 7 8 9 10

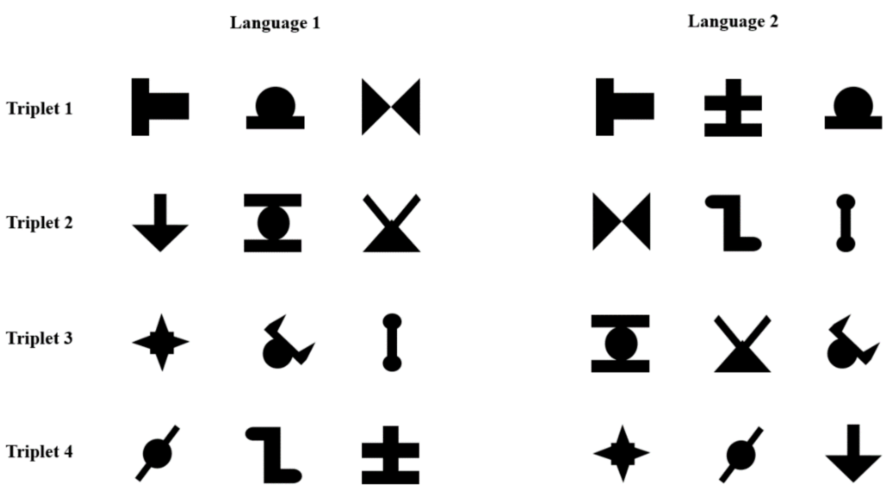
Art (if applicable) 1 2 3 4 5 6 7 8 9 10

E.6 Comparison of the two visual triplet languages used in this thesis

Triplet languages used in Chapter 3



Triplet languages used in Chapter 4-6



Appendix F: Chapter 5 additional information

F.1 Auditory statistical learning: participant information sheet, consent form and debrief

An investigation into the mechanisms of auditory sequence processing.

Information sheet

Thank you for your interest in this study.

We aim to investigate the processing of auditory stimuli in a computer- based experiment which will consist of two parts. In the first part you will be asked to simply listen to a series of tones played through headphones. In the second part you will be asked to listen to the tones again and will be asked some simple questions about them. You will also take part in a memory test and a reading test. Finally, there will be a very short questionnaire to complete.

The experiment should take no longer than 45 minutes overall and you will be granted 3 credit points for your participation.

All the information collected about you for the purpose of this study will be anonymised and kept confidential. Please remember that you have the right to withdraw your data from the study at a later stage, should you wish to do so. Please remember that you have the right to withdraw from this study at any point without providing any motivation.

This study is part of a PhD project conducted by Federica Menchinelli (fmenchinelli@lincoln.ac.uk) under the supervision of Dr Simon Durrant (sidurrant@lincoln.ac.uk) and Dr Petra Pollux (ppollux@lincoln.ac.uk).

The study has received ethical clearance by the School of Psychology Research Ethics Committee (University of Lincoln). If you have any queries about the research ethics, please contact SOPREC (School of Psychology Research Ethics) soprec@lincoln.ac.uk.

An investigation into the mechanisms of auditory sequence processing.

Consent Form

Please indicate whether you consent to taking part in this study by answering the questions below:

- I have read and understood the participant information sheet **Yes/ No**
- I confirm that I am eligible to take part in this study **Yes/ No**
- I have had the opportunity to ask any questions **Yes/ No**
- My questions have been answered satisfactorily **Yes/ No**
- I understand that:

  I am free to withdraw from the study at any time and without having to provide a reason **Yes/ No**

  All the information collected about me will be anonymised and kept confidential **Yes/ No**

- I agree to take part in this study **Yes/ No**

I agree to take part in this computer-based study. This will involve listening to a series of tones and answering some questions. I will also take part in a memory test and a reading test. I will be granted 3 credit points for my participation.

Signed (participant) ______________________________

Signed (researcher) ______________________________

Date ________________

This study is part of a PhD project conducted by Federica Menchinelli (fmenchinelli@lincoln.ac.uk) under the supervision of Dr Simon Durrant (sidurrant@lincoln.ac.uk) and Dr Petra Pollux (ppollux@lincoln.ac.uk).

The study has received ethical clearance by the School of Psychology Research Ethics Committee (University of Lincoln). If you have any queries about the research ethics, please contact SOPREC (School of Psychology Research Ethics) soprec@lincoln.ac.uk.

An investigation into the mechanisms of auditory sequence processing.

Participant Debrief

Thank you for your participation.

This experiment has tested your learning of auditory sequences with a regular structure (sequential regularities learning). Our aim is to understand the roles of implicit (unconscious) and explicit (conscious) knowledge in this type of learning.

To distinguish your implicit and explicit knowledge of the sound sequence we have used a well- established test called the Process Dissociation Procedure (PDP). You were asked to either choose the sequence that sounded more familiar (inclusion instructions) or the one that sounded less familiar (exclusion instructions). Under inclusion instructions your performance could be influenced by both implicit and explicit knowledge while exclusion performance requires explicit knowledge: you need to be conscious of knowing parts of the sequence to the able to avoid choosing them.

Whether you acquire implicit or explicit knowledge might be influenced by the speed of the sequence. We have tested this by assigning you to one of three groups with different presentation speeds: fast, medium or slow.

We also aimed to see if your working memory and reading ability are related to your ability for sequential regularities learning in this task.

This study is part of a PhD project conducted by Federica Menchinelli (fmenchinelli@lincoln.ac.uk) under the supervision of Dr Simon Durrant and Dr Petra Pollux.

For further questions contact: Federica Menchinelli (fmenchinelli@lincoln.ac.uk).

F.2 Visual statistical learning: participant information sheet, consent form and debrief

An investigation into the mechanisms of visual sequence processing.

Information sheet

Thank you for your interest in this study.

We aim to investigate the processing of visual stimuli in a computer- based experiment which will consist of two parts. In the first part you will be asked to simply watch a series of shapes presented in the centre of the screen. In the second part you will be asked to watch the shapes again and will be asked some simple questions about them. You will also take part in a memory test and a reading test. Finally, there will be a very short questionnaire to complete.

The experiment should take no longer than 60 minutes overall and you will be granted 4 credit points for your participation.

All the information collected about you for the purpose of this study will be anonymised and kept confidential. Please remember that you have the right to withdraw your data from the study at a later stage, should you wish to do so. Please remember that you have the right to withdraw from this study at any point without providing any motivation.

This study is part of a PhD project conducted by Federica Menchinelli (fmenchinelli@lincoln.ac.uk) under the supervision of Dr Simon Durrant (sidurrant@lincoln.ac.uk) and Dr Petra Pollux (ppollux@lincoln.ac.uk).

The study has received ethical clearance by the School of Psychology Research Ethics Committee (University of Lincoln). If you have any queries about the research ethics, please contact SOPREC (School of Psychology Research Ethics) soprec@lincoln.ac.uk.

An investigation into the mechanisms of visual sequence processing.

Consent Form

Please indicate whether you consent to taking part in this study by answering the questions below:

- I have read and understood the participant information sheet **Yes/ No**
- I confirm that I am eligible to take part in this study **Yes/ No**
- I have had the opportunity to ask any questions **Yes/ No**
- My questions have been answered satisfactorily **Yes/ No**
- I understand that:

  I am free to withdraw from the study at any time and without having to provide a reason **Yes/ No**

  All the information collected about me will be anonymised and kept confidential **Yes/ No**

- I agree to take part in this study **Yes/ No**

I agree to take part in this computer-based study. This will involve watching a series of shapes and answering some questions. I will also take part in a memory test and a reading test. I will be granted 4 credit points for my participation.

Signed (participant) ______________________________

Signed (researcher) ______________________________

Date ________________

This study is part of a PhD project conducted by Federica Menchinelli (fmenchinelli@lincoln.ac.uk) under the supervision of Dr Simon Durrant (sidurrant@lincoln.ac.uk) and Dr Petra Pollux (ppollux@lincoln.ac.uk).

The study has received ethical clearance by the School of Psychology Research Ethics Committee (University of Lincoln). If you have any queries about the research ethics, please contact SOPREC (School of Psychology Research Ethics) soprec@lincoln.ac.uk.

An investigation into the mechanisms of visual sequence processing.

Participant Debrief

Thank you for your participation.

This experiment has tested your learning of visual sequences with a regular structure (sequential regularities learning). Our aim is to understand the roles of implicit (unconscious) and explicit (conscious) knowledge in this type of learning.

To distinguish your implicit and explicit knowledge of the shape sequence we have used a well- established test called the Process Dissociation Procedure (PDP). You were asked to either choose the shape sequence that looked more familiar (inclusion instructions) or the one that looked less familiar (exclusion instructions). Under inclusion instructions your performance could be influenced by both implicit and explicit knowledge while exclusion performance requires explicit knowledge: you need to be conscious of knowing parts of the sequence to the able to avoid choosing them.

Whether you acquire implicit or explicit knowledge might be influenced by the speed of the sequence. We have tested this by assigning you to one of three groups with different presentation speeds: fast, medium or slow.

We also aimed to see if your working memory and reading ability are related to your ability for sequential regularities learning in this task.

This study is part of a PhD project conducted by Federica Menchinelli (fmenchinelli@lincoln.ac.uk) under the supervision of Dr Simon Durrant and Dr Petra Pollux.

For further questions contact: Federica Menchinelli (fmenchinelli@lincoln.ac.uk).

F.3 Goldsmiths Musical Sophistication Index Questionnaire (shortened version)

A shortened version of the GOLD-MSI questionnaire was used, consisting of the Perceptual Abilities and Musical Training subscales. Information about participant demographics was requested at the end of the questionnaire.

The Goldsmiths Musical Sophistication Index, v1.0

October 11, 2012

Please circle the most appropriate category:	1 Completel y	2 Strongly Di	3 Disagree	4 Neither Agree	5 Agree	6 Strongly A	7 Completel y

5. I am able to judge whether someone is a good singer or not.	1	2	3	4	5	6	7
6. I usually know when I'm hearing a song for the first time.	1	2	3	4	5	6	7

Please circle the most appropriate category:	1 Completel y	2 Strongly Di	3 Disagree	4 Neither Agree	5 Agree	6 Strongly	7 Completel y
11. I find it difficult to spot mistakes in a performance of a song even if I know the tune.	1	2	3	4	5	6	7
12. I can compare and discuss differences between two performances or versions of the same piece of music.	1	2	3	4	5	6	7
13. I have trouble recognizing a familiar song when played in a different way or by a different performer.	1	2	3	4	5	6	7
14. I have never been complimented for my talents as a musical performer.	1	2	3	4	5	6	7
18. I can tell when people sing or play out of time with the beat.	1	2	3	4	5	6	7

1

Please circle the most appropriate category:	1 Completel y	2 Strongly	3 Disagree	4 Neither Agree	5 Agree	6 Strongly	7 Completel y
22. I can tell when people sing or play out of tune.	1	2	3	4	5	6	7
23. When I sing, I have no idea whether	1	2	3	4	5	6	7
26. When I hear a piece of music I can usually identify its genre.	1	2	3	4	5	6	7
27. I would not consider myself a musi- cian.	1	2	3	4	5	6	7

Please circle the most appropriate category:

32. I engaged in regular, daily practice of a musical instrument (including voice) for 0 / 1 / 2 / 3 / 4-5 / 6-9 / 10 or more years.

33. At the peak of my interest, I practiced 0 / 0.5 / 1 / 1.5 / 2 / 3-4 / 5 or more hours per day on my primary instrument.

35. I have had formal training in music theory for 0 / 0.5 / 1 / 2 / 3 / 4-6 / 7 or more years.

36. I have had 0 / 0.5 / 1 / 2 / 3-5 / 6-9 / 10 or more years of formal training on a musical instrument (including voice) during my lifetime.

37. I can play 0 / 1 / 2 / 3 / 4 / 5 / 6 or more musical instruments.

Please tick one of the following:

Occupational status

✷ Still at School

✷ At University

✷ In Full-time employment

✷ In Part-time employment

✷ Self-employed

✷ Homemaker/full time parent

✷ Unemployed

✷ Retired

What is the Highest educational qualification you have attained?

- Did not complete any school qualification
- Completed first school qualification at about 16 years (e.g. GCSE/Junior High School)
- Completed Second qualification (e.g A levels/ High School)
- Undergraduate degree or professional qualification
- Postgraduate degree
- I am still in education

If you are still in education, what is the highest qualification you expect to obtain?

- First school qualification (e.g. GCSE / Junior High School)
- Post-16 vocational course
- Second school qualification (e.g. A-levels / High School)

* Undergraduate degree or professional qualification

* Postgraduate degree

* Not applicable

Your age : years.

Gender:

Nationality:

Do you have a diagnosis of dyslexia?

Perceptual Abilities and Musical Training subscales information

Individual items contained within the Perceptual Abilities and Musical Training subscales are displayed below

Question number	Factor 2 - Perceptual Abilities
5	I am able to judge whether someone is a good singer or not.
6	I usually know when I'm hearing a song for the first time.
11	I find it difficult to spot mistakes in a performance of a song even if I know the tune.
12	I can compare and discuss differences between two performances or versions of the same piece of music.
13	I have trouble recognizing a familiar song when played in a different way or by a different performer.
18	I can tell when people sing or play out of time with the beat.
22	I can tell when people sing or play out of tune.
23	When I sing, I have no idea whether I'm in tune or not.
26	When I hear a music I can usually identify its genre.

Question number	Factor 3 - Musical Training
14	I have never been complimented for my talents as a musical performer.
27	I would not consider myself a musician.
32	I engaged in regular, daily practice of a musical instrument (including voice) for ___ years.
33	At the peak of my interest, I practiced ___ hours per day on my primary instrument.
35	I have had formal training in music theory for __ years
36	I have had __ years of formal training on a musical instrument (including voice) during my lifetime.
37	I can play ___ musical instruments

F.4 National Adult Reading Test (NART)

Reading test (for participants)

UNIVERSITY OF
LINCOLN

Participant Number:

National Adult Reading Test

CHORD	SUPERFLUOUS
ACHE	SIMILE
DEPOT	BANAL
AISLE	QUADRUPED
BOUQUET	CELLIST
PSALM	FACADE
CAPON	ZEALOT
DENY	DRACHM
NAUSEA	AEON
DEBT	PLACEBO
COURTEOUS	ABSTEMIOUS
RAREFY	DETENTE
EQUIVOCAL	IDYLL
NAIVE	PUERPERAL
CATACOMB	AVER
GAOLED	GAUCHE
THYME	TOPIARY
HEIR	LEVIATHAN
RADIX	BEATIFY
ASSIGNATE	PRELATE
HIATUS	SIDEREAL
SUBTLE	DEMESNE
PROCREATE	SYNCOPE
GIST	LABILE
GOUGE	CAMPANILE

v1.0 01/07/2014

NART scoring sheet (for researcher)

UNIVERSITY OF LINCOLN

Participant Number:

National Adult Reading Test - Scoring

Word	Pronunciation	✓	Word	Pronunciation	✓
CHORD	kword		SUPERFLUOUS	Su **per** flu us	
ACHE	aak		SIMILE	**Sim** ill ee	
DEPOT	**dep**-oh		BANAL	**Buh** narh ll	
AISLE	**Eye**-l		QUADRUPED	**Quad** ru ped	
BOUQUET	boh-**kay** / **boo**-kay		CELLIST	Ch ell ist	
PSALM	sahlm		FACADE	Fuh **sar** d	
CAPON	**kay**-pon		ZEALOT	**Zeh** lut	
DENY	Din-**eye**		DRACHM	Dram	
NAUSEA	**Nawz** ah / **naw** zee uh		AEON	**Ee** on / **ee** un	
DEBT	det		PLACEBO	Plah **see** bo	
COURTEOUS	**Kurt** ee us		ABSTEMIOUS	Ab **stee** mee us	
RAREFY	**Rare** eff eye		DETENTE	Day **tah nt**	
EQUIVOCAL	Ee **quiv** o kul		IDYLL	**Id**-ill	
NAÏVE	**n-eye**-eve		PUERPERAL	**Pyoo ur** per uhl	
CATACOMB	Cata coom		AVER	Av **urrrr**	
GAOLED	jailed		GAUCHE	G-oh-sh	
THYME	time		TOPIARY	**Toe** pee er ee	
HEIR	air		LEVIATHAN	Leh **v-eye** a thuhn	
RADIX	**Ray** dix		BEATIFY	Be **at** if eye	
ASSIGNATE	**Ass** is nate		PRELATE	Preh lit	
HIATUS	High **ay** tus		SIDEREAL	Si **de** ree uhl	
SUBTLE	**Suh** tl		DEMESNE	domain	
PROCREATE	**Pro** cree ate		SYNCOPE	**Sing** cup ee	
GIST	Jiss t		LABILE	**Lay** bile	
GOUGE	g ow j (ow like now, how, cow)		CAMPANILE	Cam puh **nee** lee	

OVERALL SCORE (out of 50) =

v1.0 01/07/2014

F.5 Details of participants with inverted responses

Inverted responses in Chapter 3, visual triplet learning.

	Inclusion		Exclusion	
Participant anon ID	**Structured sequences**	**Unstructured sequences**	**Structured sequences**	**Unstructured sequences**
6	0.2188	0.7813	0.5938	0.4063
13	0.2813	0.7188	0.6875	0.3125
4			0.6250	0.3750
5			0.7500	0.2500
7			0.7188	0.2813
10			0.6250	0.3750
11			0.6563	0.3438

Table representing instances of inverted responses under inclusion and exclusion for our visual triplet learning experiment in Chapter 3. As evident from the table, these participants chose considerably fewer structured sequences than unstructured sequences under inclusion and vice-versa under exclusion. These instances were observed in participants who were trained with L1 as their main language. Two participants inverted their responses under both inclusion and exclusion conditions, and some participants only under exclusion conditions.

Number of participants tested = 30

Number of instances with inverted responses = 9

Inverted responses in Chapter 5, visual triplet learning

Number of participants tested = 82

Number of instances with inverted responses = 3

Appendix G: Chapter 6 additional information

The ERP correlates of implicit and explicit knowledge: participant information sheet, consent form and debrief

ERP-specific information sheet

An ERP study into the brain mechanisms of sequence processing

Information Sheet

The study

Thank you for your interest in this study.

Our aim is to investigate the brain mechanisms underlying the processing of shapes and tones. For this purpose, electroencephalography (EEG) recordings will be taken. EEG is a technique which allows to record the electrical activity generated by neurons in the brain using small electrodes which can be placed at several locations on the scalp.

Please take the time to read the following information carefully before deciding if you wish to take part. If anything is unclear, or if you would like more information, please feel free to ask.

What will happen if I choose to take part?

This is a computer- based study that will take no longer than 2 hours and will involve watching sequences of shapes on the computer screen while your brain activity is measured. The computer-based task should take no longer than 1 hour and the remaining time has been allocated for EEG setting up.

You will be asked to wear an electrode cap (similar to a swimming cap) which has several holes where electrodes will be placed to record electrical signals from different locations on your scalp. Gel will be placed on the scalp to enable the equipment to pick up the electrical activity.

For us to obtain a good recording it is essential that you sit as still as possible for the duration of the experiment.

You will receive 10 credit points in return for your participation.

What are the risks involved in participating?

There are no known risks for any of the procedures that will be used in this experiment. EEG is not painful and does not do anything to the brain. It simply allows to read electrical signals from the brain naturally arising with neural activity.

There are, however, certain requirements for participation. Please read the questions below.

Do you take any psycho-active medication?

Do you suffer from any neurological, psychiatric or sleep disorders?

Do you have a history of alcohol or drug abuse?

Do you suffer from chronic pain?

If your answer is “yes” to one or more of these questions, you will not be able to take part in the experiment.

Before coming to the experiment

In order to obtain a good signal from the EEG recording, it is important that your hair is clean and dry and that you refrain from using hair gel or other hair styling product on the day of the experiment.

After the electrode cap is removed, you will have gel residue on your scalp, so you may wish to bring a hat/ hoodie with you to wear after the experiment.

It is important that you refrain from drinking alcohol in the 24 hours preceding the experiment.

Who can I contact regarding this study?

This study is part of a PhD project conducted by Federica Menchinelli (fmenchinelli@lincoln.ac.uk) under the supervision of Dr Simon Durrant and Dr Petra Pollux.

The study has received ethical clearance by the School of Psychology Research Ethics Committee (University of Lincoln).

For further questions contact: Federica Menchinelli (fmenchinelli@lincoln.ac.uk).

Information sheet for behavioural part of the experiment

An investigation into the mechanisms of visual sequence processing.

Information sheet

Thank you for your interest in this study.

We aim to investigate the processing of visual stimuli in a computer- based experiment which will consist of two parts. In the first part you will be asked to simply watch a series of shapes presented in the centre of the screen. In the second part you will be asked to watch the shapes again and will be asked some simple questions about them.

The experiment should take no longer than 2 hours overall and you will be granted 8 credit points for your participation.

All the information collected about you for the purpose of this study will be anonymised and kept confidential. Please remember that you have the right to withdraw your data from the study at a later stage, should you wish to do so. Please remember that you have the right to withdraw from this study at any point without providing any motivation.

This study is part of a PhD project conducted by Federica Menchinelli (fmenchinelli@lincoln.ac.uk) under the supervision of Dr Simon Durrant (sidurrant@lincoln.ac.uk) and Dr Petra Pollux (ppollux@lincoln.ac.uk).

The study has received ethical clearance by the School of Psychology Research Ethics Committee (University of Lincoln). If you have any queries about the research ethics, please contact SOPREC (School of Psychology Research Ethics) soprec@lincoln.ac.uk

An ERP study into the brain mechanisms of sequence processing

Consent Form

Please indicate whether you consent to taking part in this study by answering the questions below:

- I have read and understood the participant information sheet **Yes/ No**
- I confirm that I am eligible to take part in this study **Yes/ No**
- I have had the opportunity to ask any questions **Yes/ No**
- My questions have been answered satisfactorily **Yes/ No**
- I understand that:

  I am free to withdraw from the study at any time and without having to provide a reason **Yes/ No**

  All the information collected about me will be anonymised and kept confidential **Yes/ No**

- I agree to take part in this study **Yes/ No**

I agree to take part in this computer-based EEG study. This will involve listening to sequences of sounds while my brain activity is being measured.

Signed (participant) ______________________________

Signed (researcher) ______________________________

Date ________________

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An ERP study into the brain mechanisms of sequence processing

Participant Debrief

Thank you for your participation.

This experiment has tested your learning of sequences with a regular structure (sequential regularities learning). Our aim is to discover the brain responses associated with implicit (unconscious) and explicit (conscious) knowledge in this type of learning.

To distinguish your implicit and explicit knowledge of the sequence we have used a well- established test called the Process Dissociation Procedure (PDP), which asked you to generate known parts of the sequence (inclusion instructions) or avoid generating known parts of the sequence (exclusion instructions). Under inclusion instructions your performance could be influenced by both implicit and explicit knowledge while exclusion performance required explicit knowledge: you need to be conscious of knowing parts of the sequence to be able to avoid generating them.

We have also used the speeded shape detection task as an indirect measure to assess your knowledge of the sequence structure: your reaction times to predictable shapes should be faster than to unpredictable shapes.

We will analyse the behavioural and EEG data to investigate whether implicit and explicit knowledge, as measured by the Process Dissociation Procedure and the speeded shape detection task, are associated with different brain responses.

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For further questions contact: Federica Menchinelli (fmenchinelli@lincoln.ac.uk).

Appendix H: Chapter 7 additional information

Summary table of findings

Chapter 2

Learning effect (Cohen's d)	Visual	Inclusion	N/A
		exclusion	N/A
	Auditory	Inclusion	1.526
		Exclusion	-1.389
Guessing	Visual	Inclusion	N/A
		exclusion	N/A
	Auditory	Inclusion	Explicit
		Exclusion	Explicit
Zero correlation	Visual	Inclusion	N/A
		exclusion	N/A
	Auditory	Inclusion	Explicit
		Exclusion	Explicit
Process Dissociation Procedure	Visual		N/A
	Auditory		Explicit

Chapter 3

N.B. The visual data was pooled in this experiment as there were no significant differences in performance between L1 and L2, whilst, due to significantly better performance in L2 for the auditory experiment, the two groups have been analysed separately.

Learning effect (Cohen's d)	**Visual**	**Inclusion**		**0.916**
		Exclusion		**1.072**
	Auditory	**Inclusion**	**L1**	**0.554**
			L2	**2.701**
		Exclusion	**L1**	**1.139**
			L2	**2.358**
Guessing	**Visual**	**Inclusion**		**Explicit**
		Exclusion		**Explicit**
	Auditory	**Inclusion**	**L1**	**Explicit**
			L2	**Explicit**
		Exclusion	**L1**	**Explicit**
			L2	**Explicit**
Zero Correlation	**Visual**	**Inclusion**		**Explicit**
		Exclusion		**Explicit**
	Auditory	**Inclusion**	**L1**	**Implicit**
			L2	**Explicit**
		Exclusion	**L1**	**Implicit**

			L2	**Explicit**
Process Dissociation Procedure	**Visual**			**Explicit**
	Auditory		**L1**	**Explicit**
			L2	**Explicit**

Chapter 4

N.B. This experiment was carried out on visual statistical learning only and did not use the Process Dissociation Procedure, therefore the 2AFC task was carried out under inclusion conditions only.

	Experiment version 1	Experiment version 2
Learning (Cohen's d)	0.360	0.609
Guessing	Explicit	Explicit
Zero correlation	Implicit	Explicit

Chapter 5

N.B. Cells marked as "0" indicate that the results of the criterion were not interpretable in support of either implicit or explicit knowledge.

			Fast	**Baseline**	**Slow**
Learning effect (Cohen's d)	Visual	Inclusion	0.333	0.432	0.455
		exclusion	-0.054	0.432	0.716
	Auditory	Inclusion	0.437	2.177	3.289
		Exclusion	0.211	-1.891	-3.477
Guessing	Visual	Inclusion	Implicit	Implicit[14]	0[15]
		exclusion	0	0	0
	Auditory	Inclusion	0[16]	explicit	implicit[17]
		Exclusion	implicit	explicit	explicit
Zero correlation	Visual	Inclusion	I/0[18]	I/0	I/0
		exclusion	I/0	explicit	explicit
	Auditory	Inclusion	explicit	explicit	explicit
		Exclusion	explicit	explicit	explicit
Process Dissociation	Visual		implicit[19]	explicit	explicit
	Auditory		implicit	explicit	explicit

[14] Participants performed above chance for all three knowledge attribution types. Therefore, as they performed above chance when they were guessing, this is interpreted as implicit knowledge.
[15] Participants performed at chance for all three knowledge attribution types
[16] Participants performed at chance for all three knowledge attribution types
[17] Participants performed above chance when claiming to be guessing, hence this is interpreted as implicit knowledge
[18] The lack of a difference in confidence between correct and incorrect trials could be interpreted as implicit knowledge but, in this case, the effect is more likely to be due to lack of knowledge.
[19] The one-sample t-test against chance for the inclusion condition was only marginally significant. This is a weak learning effect.