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The Relationship Between Mood and Implicit Learning

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THE RELATIONSHIP BETWEEN MOOD AND IMPLICIT LEARNING

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A dissertation submitted in partial fulfillment
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ABSTRACT

THE RELATIONSHIP BETWEEN MOOD AND IMPLICIT LEARNING

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This dissertation investigates whether a person's current mood state influences their ability to learn implicitly. Implicit learning refers to learning about regularities in the environment without having conscious access to the information (e.g., Reber, 1967). According to the *affect-as-information hypothesis*, a positive mood increases global processing of incoming information and negative mood leads to local processing (e.g., Clore & Storbeck, 2006); however, most previous studies that investigated mood and cognition have focused on more explicit types of learning and decision making, but few have examined implicit processes. Thus, the current experiments examined how varying levels of mood and arousal affect artificial grammar learning. A pilot experiment demonstrated an advantage for positive mood when the images were mood inducing. Experiment 1 had a separate mood induction phase and participants completed an artificial grammar task that contained letters. These results replicated an earlier study by Pretz et al. (2010) that showed an advantage for those in a negative mood. Experiment 2 was an expansion of the pilot by including standardized images and two additional mood groups (positive-high arousal and neutral). However, there were no significant differences between mood conditions. Experiment 3 used categories of pictures and found a disadvantage for those in a positive / high aroused state. While the patterns across the experiments were slightly different, altogether, the results were not consistent with the predictions made by the affect-as-information hypothesis. As addressed in the dissertation, this could be due to certain elements of the artificial

grammar learning procedure, such as the long viewing phase diminishing the mood and arousal induction effects. The dissertation also considers other possibilities, including the idea that implicit learning is not as affected by mood as explicit learning.

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DEDICATION

I wish to dedicate this thesis to my parents, Sherri and Joseph Larson. I am tremendously grateful for their love and support. I would also like to dedicate this thesis to my aunt and uncle, Signa and David Gundlach, who have been sources of great support and wisdom throughout the pursuit of this degree. Finally, I would like to dedicate this thesis to my former undergraduate advisor, Dr. Susan Zimny, for encouraging me to pursue post-baccalaureate study.

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CHAPTER 1

INTRODUCTION

There are many skills that people learn that they cannot always verbalize. For example, imagine a pair of police detectives were assigned to monitor the activities of a potential criminal. The detectives may learn the daily routines of the adversary after countless hours of surveillance. They may not be able to explicitly describe all of the suspect's patterns of behaviors, but they would likely notice if there is an anomaly. This dissertation explored implicit learning, where people pick up on consistent patterns without necessarily being able to describe them. In addition, this dissertation also considered how mood interacts with this process. One possibility is that a good mood will boost the ability to detect regularities due to broadening of attention that is known to accompany a positive mood (e.g., Schwarz & Clore, 2007). Another possibility is that a negative mood will increase the ability to detect anomalies due to narrowing the focus of attention (e.g., Schwarz & Clore, 2007). I will begin by discussing the construct of implicit learning, the techniques used to study it, and some of the main findings in the literature. I will then discuss mood and how it affects cognitive processes, followed by the small number of studies that have examined the influence of mood on implicit learning.

CHAPTER 2

REVIEW OF RELATED LITERATURE

Implicit Learning

Overview of Implicit Learning

Implicit learning occurs when people automatically learn information about the relations of events or objects without intending to do so, and the knowledge is difficult to express (Cleeremans, Destrebecqz, & Boyer, 1998). The procedure typically involves incidental exposure to rule governed stimuli (unbeknownst to the participant), a test to measure what participants learned, and a measure of how conscious the knowledge is that was acquired (e.g., Reber, 1967). Learning is referred to as implicit because even though people are not actively trying to encode the information for later retrieval, there is evidence that information was remembered to some degree; for example, in these tasks, participants usually score above chance on the test despite having little confidence in their performance.

The term implicit learning was first dubbed by Reber (1967) in his seminal study. Reber thought that traditional learning tasks employed in a laboratory setting did not mimic how children learn their native language. He examined language acquisition by testing adults with an artificial grammar that they had never been exposed to before. The grammar was generated by a finite-state grammar (Chomsky & Miller, 1958). This is a process where transitions from one state to another state produces a letter and is typically illustrated with a state diagram (see Figure 1). In these early experiments, grammatical strings (consisting of 3-8 letters) were presented on notecards during the learning phase. Importantly, participants were not told that the strings consisted of any pattern; they were simply told that the experiment was investigating memory.

After learning, the participants were then informed that the strings of letters were derived from a ‘rigorous’ set of rules. They then had to complete an unexpected yes / no recognition test where they decided whether the strings presented during test were grammatical. The results showed that people were able to classify the strings significantly above chance, meaning that participants were learning at least some of the rules underlying the grammar, despite not being able to state the rules in post-experimental questioning. This method has been employed in several experiments since (for reviews see Pothos, 2007; Reber, 1989; Shanks & St. John, 1994) and it now referred to as the Artificial Grammar Learning (AGL) paradigm (Reber, 1967).

Interestingly, in the late 1990’s developmental researchers coined the term statistical learning to account for a very similar phenomenon. Saffran, Aslin, and Newport (1996) had 8-month old infants listen to an artificial language where there were no pauses between words but the syllables occurred in specific temporal orders. For example, infants were presented with an audio stream such as “bidakupadotigolabubidaku” and based on the consistently repeating patterns, bidaku would be considered a “word” (note: the stimuli were audio - underlining was used here to emphasize that particular pattern for the reader). The infants listened to the language for two minutes. Then they were tested with words (e.g., bidaku) and part words (e.g., bupado); the infants looked longer at the novel words (i.e., part words), indicating that they had learned the grouping of syllables that was presented during the listening phase. The results were coined as *statistical learning* because learners could “compute” a statistic of how often the syllables occurred in relation to each other.

Statistical learning has been referred to as a type of implicit learning because learners are usually not conscious of the pattern (e.g., Aslin & Newport, 2012). There are several similarities between the statistical learning procedure and the artificial grammar paradigm. For instance, they

both require incidental learning of structured material that is followed by a test. However, there are some notable differences; specifically, for statistical learning: (1) participants are given a cover task (e.g., responding when there is a duplicate stimulus), (2) the stimuli are presented to them in one continuous stream, and (3) the recognition task is forced-choice (instead of yes / no). Despite statistical learning paradigms and artificial grammar paradigms originating from different traditions, there are now several cross-references between the two domains (see Perruchet & Pacton, 2006, for a review) and some use the term implicit statistical learning to refer to both domains (e.g., Conway & Christiansen, 2006).

Other Paradigms

Although the artificial grammar paradigm and the procedures used to examine statistical learning dominate the literature, there are two other paradigms worth mentioning. Sequence learning is a type of implicit learning that is typically measured with a Serial Reaction Time (SRT) task, where participants press a key when they see a stimulus appear in various places on the computer screen (e.g., Nissen & Bullemer, 1987). For example, the screen could be divided into a quadrant and the participant presses one of the four corresponding keys each time that a star appears. The participants are not aware that the presentation of stimuli is following a pattern, but because of the pattern, they end up making faster responses than participants who are assigned random sequences. Therefore, participants are able to predict the next event based on past events. The underlying pattern is usually generated from a finite-state grammar like those used in the artificial grammar paradigm. An advantage of the Serial Reaction Time task over other techniques is that there is no separation between the study phase and the test phase, presumably making it more like implicit learning in the real world.

Dynamic System Control is used less frequently than the other paradigms and began in the problem-solving domain. In Dynamic System Control tasks, participants are trained to control the computer simulation of an interactive system, such as a sugar factory (Berry & Broadbent, 1984). The participants are given certain output variables, such as the amount that the sugar factory produces, and have to manipulate certain inputs, such as the number of workers in the sugar factory. They are given a specific goal (e.g., amount of sugar) to reach and maintain. This task is considered implicit because participants can typically reach the goal level of control, even though they cannot explicitly state the rules of the system when asked about them in a post-experiment questionnaire. Furthermore, making participants aware of the underlying rules improves their ability to answer questions about the system but not their ability to control it (Berry & Broadbent, 1984).

Implicit Learning and Decisions in Everyday Life

Implicit learning is important to study because it is believed to be the foundation of intuitive decision making (Patterson et al, 2013). There are two types of decision processes that drive the decisions that people make: (a) analytic decision making and (b) intuitive decision making (Evans, 2008). Analytic decision making is when people make decisions in a slow and deliberate manner. For example, when someone puts a considerable amount of effort into deciding where they are going to attend graduate school, they may spend a great deal of time explicitly weighing the pros and cons of different choices. In contrast, intuitive decision making occurs when people make decisions in an automatic and procedural fashion. For example, a person's morning routine and grocery shopping involve processes that are highly automatic and typically do not involve much conscious thought. Intuitive decisions are made more than analytic decisions in order to function in everyday life.

There is often an advantage to using intuitive decision making over analytic. For example, Crandall and Getchell-Reiter (1993) studied neonatal nurses and discovered that the experienced nurses could determine whether the infants had a life threatening infection before the blood test confirmed it. However, the nurses often had difficulty verbalizing how they reached their conclusions. Similarly, physicians with a high level of knowledge can use their intuitions and make better decisions than less knowledgeable physicians (Reyna & Lloyd, 2006). Hammond, Hamm, Grassia, and Pearson (1987) found that highway engineers perform better when they use a non-analytical approach. These findings of better outcomes for intuitive decisions have been replicated in several fields, from the military to expert chess players (see Klein, 1998, for a review).

The studies above support the idea that experts can use unconscious pattern recognition to help them make quick decisions. This theory has been referred to as the Recognition Primed Decision model and posits that people make decisions, often not at a conscious level, that are based on cues in their environment that are similar to past experiences (Klein, 1997, 1998, 2008). In other words, prototypical events get stored in long term memory and the expert is able to quickly determine if the details of the current event match past events. Therefore, intuitive decision making is believed to rely on tactical knowledge that is stored in procedural memory and therefore harder to articulate (Klein, 1998). For example, a firefighter draws on past experiences to make assessments about how dangerous the fire is based on cues like heat and height of flame. Research suggests that eighty percent of the time, experts make intuitive decisions instead of analytic decisions. Experts are also more likely to spend a greater amount of time analyzing the situation as opposed to deciding a course of action compared to novices (Kobus, Proctor, Bank, & Holste, 2000).

It is important to note that not all experts can make decisions based on regularities because not all professions operate in a predictable environment. For example, stock brokers, clinical psychologists, and college admissions officers have less regularity in their jobs than firefighters, accountants, and livestock judges (Shantea, 1992). A profession like firefighting operates in an environment that has been termed “high validity” (Kahneman & Klein, 2009) because there are salient cues followed by stable events. In contrast, in a “low validity” environment, decisions are not as practiced and people often never receive feedback about their outcomes.

Due to human error in low validity environments, some have argued that statistical prediction (also termed mechanical judgments) derived from algorithms is superior to human decision making (Grove, Zald, Lebow, Snitz, & Nelson, 2000). However, as Kahneman and Klein (2009) pointed out in their review, mechanical judgments are superior to human judgments only in cases where validity is either low (so it is difficult to detect regularities) or very high (when humans are likely to have attentional lapses in judgments). In the former case, a statistical approach is more effective because it maintains consistency even when the cues are weak (Karelaia & Hogarth, 2008) because humans are more likely to find idiosyncratic relationships between variables (e.g., when predicting future stock values).

To summarize, implicit learning is an important process to study because it builds the foundation for intuitive decision making. In that, the regularities in a person’s environment that are acquired through implicit processes give people a template to compare to similar situations. Intuitive decision making is utilized in the real world more than analytic decision making. Experts in predictable environments rely on non-salient cues to make decisions but other factors can also influence how people make decisions.

Stimuli Without Words

A large number of implicit learning studies have used word stimuli, either presented visually or aurally, to better understand language acquisition. However, the use of non-word stimuli can demonstrate how we learn about other regularities in our world, outside of language. For example, both the artificial grammar paradigm and the statistical learning paradigm have been altered by replacing the “letters” in the grammar with tones (e.g., Saffran, Johnson, Aslin & Newport, 1999), images (e.g., Otsuka, Nishiyama, Nakahara, & Kawaguchi, 2013), and even vibrations (e.g., Conway and Christiansen, 2005). I will quickly review some of the research conducted in non-visual sensory modalities, but then focus on the studies that have used visual stimuli as the current investigation will use images.

Saffran et al. (1999) presented participants with nonlinguistic materials in a statistical learning paradigm. Specifically, letters were replaced with tones, such as G#DB. Adults who were non-musicians first listened to the tonal auditory streams and then made discriminations between tone ‘words’ and tone ‘part- words’ (e.g., ADB). The participants were able to successfully make the discriminations, and remarkably, so were 8-month infants in a subsequent study. This finding demonstrated that people can implicitly learn non-linguistic auditory information at a relatively low level but other studies have found that people can implicitly learn more complex auditory information such as rhythm (e.g., Selchenkova, Jones, & Tillmann, 2014).

Conway and Christiansen (2005) investigated if people could demonstrate tactile implicit learning and whether performance was comparable to other modalities. They presented vibration on participants’ fingertips in an artificial grammar sequence where each letter from the grammar

was mapped to a specific finger. Participants were able to learn the underlying structure of the vibrations, although consistent with other findings reported earlier, they were not able to verbalize the patterns. However, when the same stimulus set was compared to the auditory and visual domains, stimuli presented tactically produced comparable performance to stimuli presented visually, though aurally presented stimuli produced the best performance.

In the visual modality, implicit learning has been explored with an immersive real world environment. Patterson and colleagues (2009, 2013) examined the implicit learning of vehicles (e.g., cargo truck) in a simulated point-of-view that an Air Force pilot might encounter. The sequences of vehicles followed a finite state grammar and participants were either told to memorize or view the vehicles' sequences. Participants were able to learn the underlying grammar and the performance was comparable regardless of the instruction condition. However, when the researchers investigated participants' ability to transfer to other mediums, they found that people could transfer the knowledge of sequences from a simulated environment to a flat screen display but not the other way around. This shows that implicit learning can occur in a simulated real world environment and that there might be some slight differences between learning in a virtual environment compared to a static one.

Fiser and Aslin (2002) presented participants with an animation of changing shapes utilizing a statistical learning paradigm. One shape was presented at a time from behind a vertical cylinder. Participants were able to learn the underlying pattern as evident by 95% performance on a forced-choice recognition test and in a subsequent study they were able to also learn the conditional probabilities (e.g., that the triangle follows the star given that the square appeared). Learning the conditional probability improved with longer exposure suggesting that simpler statistics or pattern recognition are learned first.

In a study that is particularly relevant to the current investigation, Brady and Oliva (2008) examined whether people could learn implicitly at a conceptual level. Utilizing a statistical learning paradigm, they presented images of various complex scenes (e.g., bathroom, bridge, and bedroom) grouped together in triplets. Participants were very accurate on the recognition test and were able to overcome how scenes were grouped together in the real world (e.g., of those three, bathroom and bedroom are usually close in proximity in the real world). In a subsequent experiment, they used a different picture from the same category each time it was presented (e.g., covered bridge, Golden Gate bridge, etc.) and found that participants were fairly accurate, although not as accurate as when the same pictures were used. They then took it one step further and tested with only words because many of the pictures from the same category had similar perceptual features (e.g., pictures of bridges always included water). The participants performed at the same level of accuracy with the words as they did with the different pictures. The results from these experiments demonstrate that people can learn implicitly with natural scenes and that they are not just learning their low level features, but they are also processing the scenes at a higher conceptual level.

Implicit Learning Theories

Early implicit learning studies attributed implicit learning to the acquired abstract mental representations of the underlying structure of the material (e.g., Reber, 1967). This was based on the idea that knowledge in the artificial grammar task is derived from a separate, tacit system, which is why participants are often not conscious of their learning. Studies demonstrating transfer when different letters were used between training and test (Altmann, Dienes, & Goode, 1995; Mathews et al., 1989; Reber, 1969) were provided as evidence for tacit learning. Moreover, some have suggested that the information acquired through implicit learning is

consolidated in procedural memory (Patterson et al., 2013). The main evidence for this claim comes from a study where amnesic patients were able to learn pattern-analyzing skills despite showing no explicit memory for the stimuli or task (Cohen & Squire, 1980). Additionally, making participants aware of the rules before the presentation of the letter strings makes them perform worse (Reber & Allen, 1978), suggesting that an unconscious encoding might be required.

Several researchers have suggested that participants in artificial grammar experiments do not memorize rules but make decisions during the recognition test based on what has been referred to as ‘exemplars’ that were memorized during the presentation phase (Brooks & Vokey, 1991; Medin & Smith, 1981; Posner & Keele, 1968). Exemplars are derived from experiences that get stored in episodic memory as a template or schema and form the basis for category learning (Redher & Hastie, 2004). In artificial grammar paradigms, exemplars are compared to items presented on a test based on overall resemblance or similarity. In other words, people are drawing analogies between test items and exemplars that were remembered during training.

A more extreme alternative to the abstract explanation was developed by Perruchet and Pacteau (1990) who showed that the knowledge acquired in both artificial grammar learning and statistical learning tasks might consist of little more than explicitly memorized short fragments such as bigrams (i.e., two letter fragments) or trigrams (i.e., three letter fragments). Then people decide whether the grammar string presented during test is grammatical or not depending on whether it contains one of the memorized chunks. For example, a participant could recognize that the bigram TP occurs frequently and make the decision during testing that TPPTS is grammatical because it contains that memorized chunk. This explanation derives from the finding that participants who only studied bigrams performed at the same level as participants

who saw the complete letter strings (Dulaney, Carlson, & Dewey, 1984; Perruchet & Pacteau, 1990). Support for this model also comes from studies showing that grammatical test items high in ‘chunk strength’ (i.e., comprised of common bigram and trigrams) are more likely to be classified as grammatical (Knowlton & Squire, 1994).

An even more extreme theory reduces artificial grammar learning to mere exposure. The *mere exposure effect* (Zajonc, 1968) is based on the finding that people develop a preference for stimuli that they find more familiar to them. One artificial grammar study (Gordon & Holyoak, 1983) replaced the standard yes / no grammar test with a ‘liking’ test where participants rated how much they liked letter strings, and, surprisingly, performance was comparable to the standard test. Another study (Buchner, 1994) examined fluency, a similar psychological construct, where repeated stimuli are processed more quickly than novel stimuli. It was found that while people could identify grammatical strings more quickly in a perceptual clarification task, performance on that task did not predict grammatically judgments later in the yes / no recognition test. Furthermore, as mentioned previously, transfer can occur in artificial grammar learning suggesting that implicit learning is not bounded by the superficial features. Therefore, few researchers endorse the mere exposure effect as an adequate explanation of implicit learning.

Overall, researchers have not been in agreement with regards to the mechanism driving implicit learning. It could be based on a separate tacit system, a form of category learning, or based on purely memorized chunks. However, this has not been debated in the literature recently and some have suggested a hybrid explanation whereby a general tacit system and a more explicit system based on memorized details is required to be successful at implicit learning (e.g., Cleeremans, Destrebecqz, & Boyer, 2001; Meulemans & Van Der Linden, 1997).

Is Attention Needed for Implicit Learning?

On the surface, it would appear that not much attention is required to learn in an implicit learning task, considering that participants are typically not instructed to pay attention and often do not realize that they are learning anything. For example, Saffran, Newport, Aslin, Tunick, and Barrueco (1997) found that both children and adults demonstrated implicit learning with a statistical learning paradigm for auditory streams that were played in the background while they were performing an unrelated coloring task. Conway and Christiansen (2006) also used a statistical learning paradigm and found that people could learn two different sequences simultaneously if they were presented in two different modalities and performance was comparable to those that only learned one sequence. These studies have led some researchers to believe that implicit learning occurs automatically from mere exposure, thus, requiring little attention (Fiser & Aslin, 2002; Saffran et al., 1999).

However, several studies suggest the opposite; namely, that attention is required in implicit learning because a secondary task impairs performance compared to a single task when using an artificial grammar or serial reaction time paradigm (Cohen, Ivry, & Keele, 1990; Frensch, Buchner, & Lin, 1994). For instance, Patterson et al. (2013) found that accuracy suffers when people perform an implicit learning task while simultaneously engaging in articulatory suppression. The discrepancy between the Saffran et al. (1997) study and other studies possibly derives from the differences in the paradigms. Specifically, the statistical learning paradigm requires less attention due to presenting a less complex underlying pattern compared to the artificial grammar and serial reaction time paradigms. Therefore, it appears that attention helps people learn information better in an implicit learning task, but full attention may not be required.

Turke-Brown, Junge, and Scholl (2005) investigated this issue further by exploring whether attention was selective during implicit learning. Employing a statistical learning paradigm, participants were presented with green and red shapes, and told to only attend to one of the colors (e.g., “target” and “ignored” shapes). During a later test when the shapes were presented in black, people demonstrated implicit learning for the “target” shapes, but not the ones that had been presented earlier in the ignored color. The same pattern of results was found when the test included the colors that were used during the familiarization phase and when the colors were swapped (i.e., the green shapes presented during familiarization were red during the test). However, when the experimenters measured response times of target detection, participants were able to detect “target” and “ignored” shapes equally well. The results of these experiments suggest that implicit learning is automatic, but that people are able to direct their attention to particular aspects of the stimuli to improve learning.

In a later study, Turk-Browne, Isola, Scholl, and Treat (2008) were interested in whether people attend to the objects (e.g., shapes), features (e.g., color), or both during a task. Over a set of experiments, the researchers discovered that visual statistical learning can be both object-based and feature-based. When the shapes were presented in the same color during the familiarization phase, people showed better performance for objects. However, people did not show evidence of implicit learning when presented with uniquely colored shapes and then tested separately with either color patches or colorless shapes. These results indicate that implicit learning in the visual domain is more object-based but that people can still rely on features as another cue to identify the object.

Neural Correlates of Implicit Learning

Even though the experiments conducted and reported for this dissertation do not include neurological measurements, an understanding of what has been learned from studies that have focused on the brain can be helpful. Several studies have shown that amnesic patients with damage to the medial temporal lobe (which includes the hippocampus) show normal performance on an artificial grammar task (Knowlton et al., 1992; Knowlton & Squire, 1994, 1996). However, those patients are only able to perform the same as normal participants when instructed to make grammatical judgments and not when told to make judgments based on the training phase. The difference is thought to be due to the latter depending more on explicit memory processes (which are impaired for the patients due to the temporal / hippocampus damage).

Additionally, several studies have shown that patients with Huntington's and Parkinson's disease demonstrate normal artificial grammar learning (Knowlton et al., 1996; Reber & Squire, 1999; Witt, Nuhman, & Deuschl, 2002). In Huntington's disease, patients have damage to the basal ganglia (an area believed to be involved with action selection) and with Parkinson's disease, patients have damage to the substantia nigra (an area that produces dopamine). However, they do show impaired performance in the serial reaction time task, as well as other motor-related tasks (Knopman & Nissen, 1991; Siegert, Taylor, Weatherall, & Abernethy, 2006; Willingham & Koroshetz, 1993). The findings from these studies suggest that serial reaction time and artificial grammar learning may rely on different underlying mechanisms and these findings align with other studies that have found performance differences (e.g., Destrebecqz & Cleeremans, 2001).

Brain imagining studies have revealed that a large number of brain circuits are involved in implicit learning depending on the task. For instance, despite patients with Huntington's and Parkinson's performing normally on artificial grammar tasks, studies with normal participants have shown activation in the basal ganglia (Forkstam et al., 2006; Lieberman, Chang, Chiao, Bookheimer, & Knowlton, 2004). The prefrontal cortex areas, such as the left inferior gyrus and Broca's area, are involved in both the learning and testing phases in the artificial grammar paradigm (Opitz & Friederici, 2004; Petersson, Folia, & Hagoort, 2012; Skosnik et al., 2002). Interestingly, similar regions are also involved in language processing (e.g., Karuza et al., 2013).

The way that implicit learning relies on the basal ganglia is complex, in part because the basal ganglia is a multi-component system consisting of the striatum, caudate, and putamen (Nolte & Angevine, 1995). The basal ganglia are important for motor functions (e.g., eye movements; Hikosaka, Takikawa, & Kawagoe, 2000) and are connected to the motor cortex and premotor cortex (Alexander, DeLong, & Strick, 1986). However, they are also connected to the prefrontal cortex (Middleton & Strick, 1994), making it important for cognitive functions as well. There are several ways that these systems can interact in implicit tasks with learning taking place in either the basal ganglia (Pasupathy & Miller, 2005) or the prefrontal cortex first (Fuster, 2001).

Overall, the neurological underpinnings that underlie implicit learning are complex. The hippocampus is generally associated with explicit long term memory but does not appear to play a role in implicit learning, as evident by amnesiacs' normal performance (e.g., Knowlton and Squire, 1994). The basal ganglia appear to be an important set of structures for implicit learning (e.g., Forkstam et al., 2006), but reliance on them is not absolutely necessary as those who have damage to their basal ganglia (e.g., those with Parkinson's and Huntington's disease) still

perform normally on artificial grammar tasks, probably due to the recruitment of another brain structure such as the prefrontal cortex (Fuster, 2001).

Individual Differences and Implicit Learning

In cognitive psychology, it is common to explore individual differences in cognitive processes; however, the cognitive processes that are examined are usually more explicit. For example, individual differences in an explicit task like a working memory span test are related to performance on other explicit cognitive tasks, such as IQ, problem solving, and comprehension (Conway, Cowan, Bunting, Theriault, & Minkoff, 2002; Engle, 2002). In contrast, numerous studies have found modest to no correlations between implicit learning and individual differences in cognitive abilities such as working memory, intelligence, and intentional associate learning (Gebauer & MacKintosh, 2007; Kaufman et al., 2009; McGeorge, Crawford, & Kelly, 1997; Reber, 1993; Reber, Walken, & Hernstadt, 1991). Some researchers have posited that the lack of individual differences stem from implicit learning being more of an evolutionarily older ability and thus should be more resistant to individual differences (Reber, 1993). However, others have gone as far to say that implicit learning tasks are more dependent on automatic association processes rather than cognitive abilities (e.g., Mackintosh, 1998), which is in line with many dual process theories that are considered today (Chaiken & Trope, 1999; Epstein, Pacin, Denes-Raj, & Haier, 1996; Evans, 2003,2008; Evans & Stanovich, 2013).

Despite the lack of correlations between implicit learning task performance and traditional individual difference variables in cognition (e.g., working memory, IQ, etc.), relationships have been observed when using nontraditional variables. Specifically, Kaufman et al. (2010) found that verbal analogical reasoning and foreign language performance

independently predicted performance on a serial reaction time task in adolescents. This finding suggests that implicit learning ability might contribute to specific language acquisition skills and is consistent with findings in the statistical learning literature which have found that higher performance on statistical learning tasks in children is related to learning the syntax of language (Kidd, 2012), reading ability (Arcului & Simpson, 2012), and vocabulary growth (Evans et al., 2009).

It also appears that implicit learning proficiency may be related to certain facets of personality. One study found that individuals who were categorized as intuitive types on the Myers-Briggs Type Indicator (Jung, 1971) were better than sensing types at the implicit learning task of judging applicant personality profiles (Woolhouse & Bayne, 2000). The intuitive types also reported using more intuitive strategies than the sensing types. The researchers suggested that perhaps the intuitive types let feelings of familiarity guide their decisions. Kaufman et al. (2010) also found a relationship between intuitive personality type and implicit learning with a serial reaction time task. Additionally, performance on the serial reaction time task was also correlated with the Openness aspect of the Big Five Aspect Scales (DeYoung, Quilty, & Peterson 2007). Other researchers have also argued that intuition and implicit learning are related constructs with subjective feelings getting acquired through implicit learning experiences (Dienes, 2008; Lieberman, 2000; Reber, 1989).

Individual differences arising from differences in culture background have also been examined. It is well known that Westerners are more focused on individual elements and Asians focus more on global aspects or the 'big picture' (e.g., Nisbett, 2003). Kiyokawa, Dienes, Tanaka, Yamada, and Crowe (2012) presented grammatical strings consisting of large letters that was made of a smaller, different letter (e.g., a large N made up of smaller B's) to Japanese

(Asian) and United Kingdom (Western) participants. The researchers found that the Japanese learned only at the global level but the United Kingdom participants learned equally well at both levels. In a subsequent experiment, when participants were instructed to attend to the global or local level, the participants from both cultures performed equally.

Overall, it appears that implicit learning is related to other psychological processes that are relatively implicit, especially those that are related to language learning (e.g., Kaufman et al., 2010). However, being both open to experiences and more likely to rely on feelings of intuition are also related to better performance on implicit learning tasks (e.g., Woolhouse & Bayne, 2000). These findings suggest that occupation selection in terms of personality tests and language learning proficiency may be a useful tool to judge who is going to perform well at tasks involving implicit processes. A person's mood might also influence implicit learning. The next section will discuss how a person's current emotional state or mood influences how they make decisions, perceive the world, and what they encode in their memory.

Mood

Overview of Mood

When using the term *mood*, it is important to note that there are several different, related terms that can be used and have been used by researchers to describe this phenomenon. *Affect* is the term used to refer to the representation of general valence that one experiences and it can be positive or negative. The representation can be cognitive, physiological, and behavioral, among others (Clore & Huntsinger, 2007). *Mood* is a similar term that refers to a diffuse affective state. In contrast, *emotions* are usually seen as related to the appraisal of a single object or stimulus, shorter in duration, and can be reflected differently depending on the type of emotion being

expressed (Clore & Huntsinger, 2007; Eldar, Rutledge, Dolan, & Niv, 2015). While some researchers have used the term affect (e.g., Isen, 2002), and others have used mood (e.g., Gasper & Clore, 2002), the terms appear to be relatively synonymous and used interchangeably in the literature.

There are several ways that mood can be induced in a laboratory setting. For example, mood state can be manipulated by having participants watch films, recall memories, view pictures, or listen to music. Additionally, the mood manipulation procedure can be considered incidental, referring to when the mood state is not related to the cognitive task. It can also be integral, referring to when the mood state is induced by the cognitive task (e.g., making judgments about car accident pictures). To my knowledge, there are only a handful of studies comparing the different mood induction procedures (Albersnagel, 1988; Martin, 1990; Westermann, Spies, Stahl, & Hales, 1996). A meta-analysis that examined 11 of the mood induction procedures found larger effect sizes for film and story (Westermann et al., 1996). The effects are also larger when participants are explicitly told to enter a mood state, indicating that participants are possibly succumbing to demand characteristics (Westermann et al., 1996).

When researchers ask participants to self-report mood, the most widely used mood measure is the Positive And Negative Affect Schedule (PANAS) which consists of 10 positive mood words (e.g., excited) and 10 negative mood words (e.g., distressed) that participants rate on a five point Likert scale (Watson, Clark, & Tellegen, 1988). It was derived from Zevon and Tellegen's (1982) larger mood checklist and has been found to be reliable, valid, and not influenced by demographic variables (Crawford & Henry, 2004). It is typically administered before and after the mood induction procedure to see if the induction impacted their baseline mood state. Because certain cognitive effects, especially in decision making, are reduced if

participants are aware of the mood manipulation (e.g., Schwarz & Clore, 1983), briefer versions of the PANAS were explored. For example, a short form of the measure (I-PANAS-SF) was developed a few years ago and consists of only 5 positive and 5 negative words (Thompson, 2007). The shorter version was found to be a reliable and valid research tool that does not take as long to administer as the traditional PANAS.

Mood and Cognition

An important reason for discussing the effects of mood is that research has shown that the mood an individual is experiencing can influence how they learn and process information and this has been termed the *affect-as-information hypothesis* (Clore & Storbeck, 2006; Schwarz & Clore, 1983, 2007). Specifically, a positive mood is believed to elicit *relational processing* and involves processing incoming information in relation to concepts in memory and drawing connections between those related concepts (Fiedler, 2001; Hunt & McDaniel, 1993). To put it simply, a positive mood encourages a broadening of attention and cognitive resources, leading people to focus on the big picture rather than the details. As a result, a positive mood encourages the use of schemas (Bodenhausen, Kramer, & Suesser, 1994), promotes the solving of insight problems by increasing transfer (Rowe, Hirsch, & Anderson, 2007), and focuses attention on the global aspects of stimuli (Gasper & Clore, 2002).

However, drawing these global connections as a result of being in a good mood can be a disadvantage, depending on the goal of the task. As an example of this, Storbeck and Clore (2005) induced mood through music and then had participants complete the Deese-Roediger-McDermott (DRM) paradigm. In this paradigm (Roediger & McDermott, 1995), participants are presented with a list of related words (e.g., freeze, shiver, arctic) that are missing one highly

associated word (e.g., cold), which is referred to as the critical lure. If participants incorrectly recall the critical lure as part of the original list, they are thought to have constructed a false memory. In the Storbeck and Clore (2005) study, participants in a positive mood were more likely to recall the critical lures; in other words, these participants, who were in a positive mood, formed the association between the list of related words and the critical lure, leading them to mistakenly recall the critical lure. It should be noted, though, that a later study demonstrated this trend only occurs when the mood induction procedure is performed before participants study the list of words (Storbeck & Clore, 2011), suggesting that the association made (due to the positive mood) occurred during encoding (i.e., not retrieval).

In contrast to the research on positive moods, a negative mood can prevent false memories due to what has been termed *item specific processing* (Brainerd & Reyna, 1998; Fiedler, 2001; Hunt & McDaniel, 1993). This involves processing the unique features (or details) of stimuli, rather than considering the stimuli in relation to other concepts. Because those in a negative mood are less likely to make connections among related concepts, they are less likely to be susceptible to false memories (Storbeck & Clore, 2005), the influence of scripts (Bless et al., 1996), and the reliance on stereotypes (Isbell, 2004); in other words, they are making fewer inferences or connections. In contrast to a positive mood, a negative mood enhances memory for specific details that are in one's focus (Kensinger, Garoff-Eaton, & Schacter, 2007), analytical thinking (Bless, Bohner, Schwarz, & Strack, 1990), performance on deductive reasoning tasks (Oaksford, Morris, Graniger, & Williams, 1996) and improves performance on spatial tasks (Gray, 2001).

Not surprisingly, because mood influences the focus of attention, it also impacts what is remembered about the stimuli or the event itself. Specifically, a vast amount of research suggests

that a positive mood increases memory for extrinsic contextual details and a negative mood increases memory for intrinsic item features (for a review, see Kensinger, 2009). For instance, studying an image of a car accident (i.e., a stimulus inducing a negative mood) will produce high accuracy for the accident but not for the surrounding context, such as the street where the accident occurred (Buchanan & Adolphs, 2002; Reisberg & Heuer, 2004). The visual details of negative items (e.g., snake) are also more likely to be remembered than positive items (e.g., cake) (Kensinger, Garoff-Eaton, & Schacter, 2007; Kensinger & Schacter, 2008). The lack of encoding for details can carry over to stimuli or events presented shortly after, such as a negative word blocking the memory for the subsequent word (Hurlemann et al., 2005).

While the studies mentioned above used stimuli that can clearly be put in a positive or negative category, the trends hold up even when the valence of the event is determined by the perceiver. For example, after a professional baseball game in which the Red Sox beat the Yankees, the Yankees fans (who were in a negative mood due to their team losing) remembered event details more accurately (Kensinger & Schacter, 2006). Additionally, Germans who did not support the fall of the Berlin Wall (and, hence, were in more of a negative mood) reported more accurate details about the event (Bohn & Berntsen, 2007). Similarly, people who disagreed with the verdict in the O.J. Simpson trial were less likely to “falsely” recognize fictitious events from the trial; in other words, being in more of a negative mood was related to them being more accurate (Levine & Bluck, 2004). These findings all support the affect- as-information hypothesis in real word scenarios, with individuals in a negative mood focusing more on the details which results in stronger memory of those details to a greater extent than those in a positive mood.

Although negative mood draws attention away from contextual details so that attention can be focused on the mood inducing stimuli, sometimes this memory trade-off can be overcome when people are given specific encoding instructions. In one study, when young adults were instructed to remember all aspects of an accident scene (i.e., have a broader focus) they were able to overcome the usual narrowing of attention that accompanies a negative mood; however, it should be noted that older adults still had a narrow focus and were unable to remember the contextual details (Kensinger, Piquet, Krendl, & Corkin, 2005). This finding suggests that it is possible that people can be trained to have a broadening of attention with some negative stimuli but that it does require extra cognitive resources, which is why older adults were unable to overcome the deficit.

It is important to point out that the research reviewed so far focuses on the valence of mood, or the general state of feeling positive or negative. However, recent research has found that motivational direction should also be considered (e.g., Harmon-Jones, Gable, & Price, 2013). Motivational direction is the degree to which a particular affective stimulus encourages a behavior. For example, viewing a cat film is considered low approach while viewing desserts is considered high approach (Gable & Harmon-Jones, 2008). This is because while most people find cat films entertaining, it does not encourage them to take any action; in contrast, seeing an appealing food typically makes people hungry. This motivational direction changes the focus of attention, making those who watch the dessert film have a narrower focus on a visual processing task. Furthermore, the attention is narrowed even more when participants are told that they will be able to consume the desserts after viewing the pictures. Therefore, the usual broadening of attention does not occur when people are motivated to perform a behavior. Although, this

dissertation will be focusing on valence, motivational direction will be considered when choosing stimuli.

Altogether, a body of evidence demonstrates that mood changes how people process and remember information. Because the studies highlighted above all involve explicit memory, learning, and problem solving tasks, the question remains whether mood influences implicit learning. The affect-as-information hypothesis is based on the idea that attention gets altered by mood, thus influencing learning and memory outcomes. However, as previously reviewed, attention is tied to better implicit learning performance, but full attention is not required. Therefore, it is possible that mood may not change how people perform on an implicit learning task. Also, it is hard to predict whether a global focus or narrow focus would be optimal for implicit learning performance. In the next section, I review the dimension of arousal, how it interacts with mood, and how it influences cognition.

Arousal

While the majority of studies, especially in the cognitive realm, have focused on valence (i.e., general direction of mood), arousal is another dimension that should be considered. Arousal refers to the level of excitement that characterizes the dimension. For example, a picture of a garden elicits feelings of pleasantness (i.e., valence) but also calmness, which is low in arousal. In contrast, a picture of skydiving elicits feelings of both pleasantness (i.e., valence) and excitement, which is high in arousal.

Arousal is often measured by having participants rate stimuli (e.g., images) with the Self-Assessment Manikin (SAM; Lang, 1980). Participants rate their arousal level on a 1 to 9 scale, with a 1 representing calm / unaroused and a 9 representing excitement / aroused. The number

scale is accompanied by images of a cartoon character depicting various levels of arousal (see Figure 2) because the pictures allow the scale to be presented to children and those from different cultures. To gather data about valence, it is often presented concurrently with a similar scale that has one extreme representing pleasant / happy and the other representing unpleasant / unhappy.

In addition to mood, arousal is another aspect that influences how we perceive our environment and remember experiences. In general, arousal is known to enhance memory for details by focusing attention (Cahill & McGaugh, 1998; Hamann, 2001), such as what occurs during the *weapon-focus effect* where eye witnesses focus on the weapon and then remember fewer details about other objects or people (Loftus, Loftus, & Messo, 1987). While most research has used stimuli that are both arousing and valent, a few studies have shown that arousal is not always needed to enhance memory (Kensinger & Corkin, 2003, LaBar & Phelps, 1998; Ochsner, 2000). This disassociation is believed to occur because valence and arousal rely on different memory processes. Arousal increases consolidation processes due to the recruitment of the amygdala while non-arousing stimuli rely more on elaborate encoding processes (for a review, see Kensinger, 2004).

The interplay of arousal and valence is complex and disputed and there are a few models that account for both arousal and valence. The circumplex model (Barrett & Russel, 1998; Posner, Russell, & Peterson, 2005; Russel, 1980) proposes that arousal (referred to as activation) and valence are independent dimensions and that the core emotions of each category can be fitted around the perimeter of a circle at 45 degree increments, resulting in different types of positive and negative moods. For example, on the one hand, graduate students could be in an elated mood because they just passed their dissertation proposal. It is likely that they have a high level of arousal because they are excited about completing a goal and that they also have a high level of

valence because the successful proposal put them into a good mood. On the other hand, those same graduate students could also be in a good mood but not be activated (i.e., calm) if they were relaxing at the spa the day after their defense. A second account of arousal and valence (Watson, Wiese, Vaidya, & Tellegan, 1999) proposed that the dimensions are more of a hierarchy with valence being the primary dimension at the top followed by the arousal dimension in each valence category. While there is disagreement surrounding how these dimensions are related, both accounts agree that valence and arousal are separate dimensions.

While arousal has not been the focus in studies examining mood and explicit learning, it is very relevant to implicit learning because many of the stimuli used in studies, particularly the negative stimuli, are inherently arousing. Thus, it is possible that arousal, which has not been measured in earlier studies, could contribute to performance. Because of this, arousal will be considered in the design of these dissertation experiments. In the next section, I review the few studies that have investigated mood and implicit processes.

Mood and Implicit Learning

To date there have been very few studies that have examined the relationship between mood states and implicit learning and, unfortunately, the results of these studies are somewhat mixed. For instance, there is a discrepancy with the findings for the two studies that examined mood and the serial reaction time task. On the one hand, Pretz, Tetz, and Kaufman (2010) had participants perform a serial reaction time task after viewing mood inducing pictures and found no differences between mood groups. On the other hand, Shang, Fu, Dienes, Shao, and Fun (2013) found that participants in a positive mood, as induced with music, performed better in a serial reaction time task. The researchers noted the discrepancy between their results and the

Pretz et al. (2010) study by emphasizing that Pretz et al. (2010) (a) used a more complex sequence and (b) the mood induction procedure was different in that Pretz et al. (2010) used images instead of music. The Shang et al. (2013) findings align well with the affect-as-information hypothesis (Scharz & Clore, 1983), which postulates that positive mood increases access to prior knowledge in explicit learning tasks.

In a different study, Bertels, Demoulin, Franco, and Destrebecqz (2013) induced mood aurally through stories while simultaneously presenting participants with shapes in a statistical learning paradigm. Participants performed a forced-choice recognition test, which is usually employed in statistical learning tasks, along with a Rapid Serial Visual Presentation (RSVP) task where participants had to identify targets from the exposure phase among distractors as quickly as possible. While the negative mood group and neutral group (there was no positive mood group) performed similarly, even after a 20 minute delay, the negative group was more confident in their decisions (i.e., less likely to report guessing). However, as the authors suggested, it is possible that the negative group were paying more attention to the stimuli in order to avoid listening to the negative story.

Another study examined the effect of mood on the detection of covariation, which is a process that can lead to implicit learning (Braverman, 2005). Participants' moods were induced through movie clips and they then viewed faces that were accompanied by verbal (e.g., 80) and math scores (e.g., 20) on a hypothetical test. Math and verbal scores were chosen because the researcher believed that neither was related to stereotypes. The participants were instructed to pay attention to which score was higher. Unbeknownst to the participants, nose size was correlated with scores (i.e., a higher math score was correlated with a larger nose). Participants then had to take a test with new faces and guess which score was higher. Participants in the

negative mood group detected the covariation more often than the positive group, and the effect remained even after removing the participants who noticed the covariation. Subsequent experiments found that including a digit string task, thus adding cognitive load, made the effect less powerful, and increasing motivation via a reward eliminated the differences between the mood groups. This set of experiments demonstrate that mood affects the detection of covariation, but that other factors such as motivation and the cognitive demands of the task can also influence the ability to detect covariation in one's environment.

Depression could be considered a more long lasting mood state so it makes sense to examine how depressed individuals perform on implicit learning tasks. There have been a few studies examining this relationship, but there is again somewhat of a discrepancy with the findings. Two studies examined mild depression with implicit learning on an artificial grammar task (Rathus, Reber, Manza, & Kushner, 1994) and a serial reaction time task (Pedersen et al., 2009) but found no differences compared to healthy controls. However, two other studies found that those with moderate to severe depression had worse performance on serial reaction time task compared to controls (Naismith, Hickie, Ward, Scott, & Little, 2006; Naismith et al., 2010). It is important to mention that the participants in the Naismith et al. (2006) study also performed worse on neuropsychological tests, such as visuomotor speed, so it is possible that general cognitive deficits were driving performance on the implicit learning measures.

Pretz et al. (2010) have been the only researchers to study the effect of mood (not related to being clinically depressed) on implicit learning with an artificial grammar paradigm. They induced mood by having participants view 50 pictures from the International Affective Picture System (IAPS) (Lang, Bradley, & Cuthbert, 1997) to either induce a positive, negative, or neutral mood and then memorized 20 letter strings from Reber's (1967) artificial grammar. They

were tested with 50 grammatical strings; 7 were from the original set, 19 were consistent with the grammar, and 24 were non grammatical. Although the authors predicted a positive mood would facilitate implicit learning, they found the opposite, where negative mood facilitated grammar learning with participants in the negative mood condition outperforming those in the positive and neutral condition. The researchers suggested that perhaps a more analytic style of thinking is more conducive to performing well on implicit learning tasks and pointed out that implicit learning does not rely on heuristics or schemas (which a positive mood is known to increase the use of).

In summary, there have only been a handful of studies that examined mood and implicit learning processes and only one of these studies used an artificial grammar. The two studies utilizing the serial reaction time paradigm have conflicting findings, with one finding significant differences (Bertels et al., 2003) and the other no significant differences (Pretz et al., 2010). Overall, these studies demonstrate that more research needs to be conducted to determine whether mood influences implicit learning.

CHAPTER 3

EXPERIMENT OVERVIEW

The purpose of this dissertation was to examine whether mood influences implicit learning. As described in the previous section, the few studies that have been conducted have provided no clear consensus as to whether or how mood influences implicit learning. Of particular interest to the current investigation, only one study has used an artificial grammar paradigm (Pretz et al., 2010). I think it is important to more thoroughly investigate the relationship between mood and implicit learning to determine whether people's mood can have bearings on how they perceive relationships in their environment and what mood state may be more beneficial for optimal performance in a setting where it may be crucial to learn patterns in the environment.

To explore the impact of mood on implicit learning, I employed an artificial grammar paradigm where mood inducing images were used instead of letters. Therefore, the mood induction procedure is integral, meaning that the mood state is related to the cognitive task. In contrast, Pretz et al. (2010) used an incidental mood manipulation procedure, first having participants view mood pictures and then study strings of letters. An integral mood manipulation procedure was chosen in the current investigation to simulate how affective objects / stimuli in one's environment may influence learning. For example, if a soldier witnessed an Improvised Explosive Device (IED) harm some of his comrades, will he have learned the cues in the environment to next time pick up on the cues that lead to the IED explosion?

Due to the little research that has been conducted in the area and because the proposed method differed substantially from Pretz et al. (2010), a pilot study was conducted first. As a

preview of those results, the opposite trend as Pretz et al. (2010) was found, in which a positive mood increased implicit learning on an artificial grammar task. One possibility is that the type of mood task used (i.e., integral versus incidental) might predict how mood interacts with implicit learning. However, because it is not yet known what is driving the discrepancy, Experiment 1 attempted to replicate the exact Pretz et al. (2010) experiment as closely as possible by following the methods from that paper, to see if the same trend is obtained. Therefore, in Experiment 1, participants viewed pictures, then viewed letters derived from the Reber (1967) study, and then took a grammar test.

Experiment 2 built upon and improved the pilot experiment. This also served as another test to examine whether the Pretz et al. findings were an anomaly. The key manipulation in Experiment 2 was whether the images were positive, neutral, or negative. In addition, arousal was taken into account and two positive groups were created: positive-high arousal and positive-low arousal. Unlike in the pilot experiment, all images were selected from the International Affective Picture System (IAPS) (Lang, Bradley, & Cuthbert, 1997), which is a database of standardized images that have been used in several mood studies. Examples of positive images are puppies, ice cream, nature scenes, and depictions of romantic relationships. Examples of negative images are poverty, animal abuse, and death. Neutral pictures include depictions of mundane objects such as a trains, satellites, or clocks.

The other manipulation in Experiment 2 was whether the participants received a training phase or not. The training phase refers to the presentation phase where participants are exposed to the grammar, which is an essential component of the artificial grammar paradigm. The benefit of having a condition where participants only complete the test ensures that the grammar is not explicit enough that people can detect the underlying pattern without a presentation phase.

Therefore, including a test-only group serves as a control and this method has been employed in recent implicit learning studies (e.g., Covas-Smith, 2011; Patterson et al., 2011).

Based on studies that have looked at mood and more explicit types of learning (e.g., Gasper & Clore, 2002), as well as the pilot study results, it was predicted that a positive mood would produce higher implicit learning scores. Specifically, according to the affect-as-information hypothesis, a positive mood encourages relational processing, indicating that participants in a positive mood would be more likely to process incoming information in relation to other concepts presented around it. Based on what has been observed in previous studies, it is possible that the broadening of attention will be beneficial in picking up the regularity of the grammar. However, a somewhat weaker case could be made for a negative mood making people better at implicit learning tasks as was demonstrated in the Pretz et al. (2010) study. If this pattern were observed, it would be because the narrowing of attention might help people learn the exemplars or chunks better. Because of the larger number of studies showing benefits of positive mood for making connections, the former outcome is thought to be more likely.

The second goal of this investigation was to examine whether mood would influence the ability to learn at a categorical level. Similar to Experiment 2, Experiment 3 also presented mood inducing images with an artificial grammar paradigm; the major difference was that instead of repeating the same (i.e., identical) pictures, Experiment 3 presented similar, but different pictures to represent the same 'letter'. For example, in Experiment 2, the same cute puppy picture was shown each time to represent a designated 'letter' in the sequence. However, in Experiment 3, a different puppy was shown each time that 'letter' is presented in a sequence. This is similar to the paradigm that Brady and Oliva (2008) employed except that they used a statistical learning paradigm and their images were not mood inducing. It could be argued that this design resembles

implicit learning more in real world setting where a particular object / person / situation is not likely to be exactly the same, but might come from a similar category.

In Experiment 3, it was hypothesized that the positive mood group would also demonstrate higher overall performance on the implicit learning test. The Brady and Oliva (2008) study found evidence of people being able to learn rather easily at a categorical level. While they did not manipulate mood, research looking at mood and explicit learning has found that relational processing tends to be humans' default style of processing (e.g., Gasper & Clore, 2002). Therefore, it was speculated that the negative group will perform worse than the other groups (i.e., the two positive groups and the neutral group), and that the differences might be more extreme than in Experiment 2 due to the use of different pictures especially relying on drawing connections between incoming information.

CHAPTER 4

PILOT EXPERIMENT

Given the small number of studies that have been conducted in the area of implicit learning and mood, a pilot study was conducted to serve two purposes: 1) to first examine whether there would be a difference between the mood groups, and 2) to determine whether the complexity of the grammar would make a difference in participant performance. As a reminder, although Pretz et al. (2010) used an artificial grammar paradigm, they did the mood induction separately from the training phase, and the artificial grammar task consisted of letters. This pilot experiment was different in that the mood inducing pictures followed a finite state diagram; in other words, the training phase and the mood induction were the same phase of the experiment. Furthermore, because the Pretz et al. (2010) results do not necessarily line up with the patterns observed by other studies investigating the affect-as-information hypothesis, there was a need to replicate their experiment before pursuing it for dissertation work.

Method

Participants

A total of 146 participants were recruited from the subject pool at the University of Nevada, Las Vegas. Within the simple grammar condition, 34 participants were randomly assigned to the positive mood group in the simple grammar condition and 32 to the negative mood group. Within the complex grammar condition, 42 were randomly assigned to the positive mood group and 37 to the negative mood group. Participants were issued research credit for their psychology course. All participants were able to fluently speak and comprehend English.

Materials

Pictures depicting positive and negative moods were selected from the internet. These pictures were rated by two individuals (the experimenter and a graduate student) in terms of positive and negative mood inducement; only pictures that were rated as clearly positive and clearly negative by both raters were included in those categories – any pictures with a discrepancy of opinion were not used (see Appendix B for a complete set of the images). The Positive And Negative Affect Schedule (PANAS) was used for the mood manipulation check (Watson et al., 1988). The PANAS contains 10 positive mood words (e.g., alert) and 10 negative mood words (e.g., upset) (see Appendix C for a complete set of items). As mentioned previously, the PANAS is the most widely used mood measure and is found to be highly reliable and valid (Crawford & Henry, 2004).

The order of the pictures was determined using a finite state diagram. For the simple condition, the Reber (1967) artificial grammar was used (see Figure 1). For the complex condition, a modified version of the Reber and Allen (1978) grammar was used (see Figure 2). A picture was selected to represent each of the nodes (see Figures 3, 4, 5, and 6) in the same manner that letters were assigned to nodes in the Reber (1967) and Reber and Allen (1978) studies. The mood image sequence begins when the diagram is entered on the left and ends when the diagram exits on the right. Therefore, the length of the sequence can vary depending on the paths that are followed through the diagram. However, the length of each sequence was restricted to between 4 and 9 nodes. For example, one sequence might be mountain, dessert, mountain, and old couple if a path was followed along 0120'; another might be baby, dog, dog, baby, dessert, and old couple if a path was followed along 03420'.

The sequences that were produced are referred to as the ‘structured set’ (see Appendix D for a list of the full set). Quasi-random sequences were generated and presented during test. These sequences are referred to as the ‘unstructured set’. The random sequences were generated by fixing the beginning and end of the sequences but scrambling the middle portion to discourage judgments during the recognition test being based on rules learned.

Procedure

After the consent process, participants completed the Positive And Negative Affect Schedule (PANAS) (Watson et al., 1988) on Qualtrics (Qualtrics, Provo, UT) to determine their baseline mood state. The participants then watched positive or negative picture sequences on a PowerPoint presentation for 5 seconds per sequence with 1 second pauses between the sequences. The mood induction and the training phase of the implicit learning task was the same. In other words, the mood induction procedure was integral, in that the stimuli themselves were mood inducing. Similar to other implicit learning studies (e.g., Patterson et al., 2013), participants were not told to direct their attention or to memorize the stimuli, nor were they given feedback. However, for ethical reasons, participants in the negative mood group were told that some of the pictures may upset them and reminded that they can quit the experiment at any time. The order of the pictures was determined using a finite state algorithm but the same order was used for every participant in the negative condition and the same order was used for every participant in the positive mood condition. Twenty sequences were presented 16 times, leading the presentation phase to be approximately 30 minutes.

After the training phase, participants immediately completed the PANAS again to ensure that the mood manipulation procedure was effective. They were then informed that the pictures

they just viewed were following an underlying pattern. They were administered a yes / no recognition test on paper where they circled ‘yes’ for the picture sequence being structured (i.e., consistent with the pattern) and circled ‘no’ for the picture sequence being unstructured (i.e., inconsistent with the pattern). The test consisted of a total of 60 sequences: 20 sequences that were previously presented, 20 sequences that were novel but consistent with the finite-state grammar, and 20 random sequences (i.e., foils). The order of the sequences was randomized but was the same order for every participant. After the test, participants were thanked, debriefed, and given credit for their participation.

Results

PANAS

The positive group had a positive affect score on the PANAS of 31.11 and a negative affect score of 17.91 after the presentation phase. The negative mood group had a positive affect score of 27.12 and a negative affect score of 28.50. It is unknown why the negative mood group retained such a high positive affect score but one possibility is that due to the mere exposure effect, perhaps viewing the same pictures several times, albeit negative, made people slightly more positive. However, there were still performance differences between the groups (as noted below).

Grammar Test

For the simple grammar, the recognition test revealed that overall accuracy was 63.333%. An independent-samples t – test was performed between the positive and negative mood groups, with the positive mood group ($M = 66.970\%$, $SE = 1.391$) outperforming the negative mood

group ($M = 60.016\%$, $SE = 1.711$), $t(64) = 2.811$, $p = 0.007$. For the complex grammar, the overall accuracy on the recognition test was 52.350%. An independent t – test performed between the mood groups revealed that the positive mood group ($M = 54.683\%$, $SE = 1.484$) again outperformed the negative mood group ($M = 50.181\%$, $SE = 1.182$), $t(77) = 2.33$, $p = 0.022$ (see Figure 8).

Discussion

These results demonstrated that there were significant differences between mood groups in both grammar conditions, which demonstrated that this area of research is a worthwhile pursuit for dissertation work. However, interestingly, the results were in the opposite direction than what was observed in the Pretz et al. (2010) study, but they are more consistent with the affect-as-information hypothesis. As a reminder, unlike the earlier study, the mood induction process here was integral, so it is possible that this contributed to the current findings being different than the Pretz et al. (2010) study (which induced mood separate from the learning phase). One possibility is that because a certain amount of attention is required to implicitly learn, perhaps the negative images made those in the negative condition not direct less attention to the patterns. Another possibility is that the unique pictures that were chosen for the pilot was driving the effect and perhaps this effect would not be observed with standardized images. Finally, another possibility is that the Pretz et al. (2010) results were an anomaly; this possibly as well as other factors that may influence implicit learning were explored more in the following experiments.

CHAPTER 5
EXPERIMENT 1

Method

Participants

A total of 114 participants were recruited from the subject pool at the University of Nevada, Las Vegas; none of them participated in the pilot experiment. Thirty-eight participants were in each of the three mood groups: positive, negative, and neutral (this n is similar to the number of participants that participated in the Pretz et al. (2010) study which had a sample size of 109). Participants were issued research credit for their psychology course. All participants were able to fluently speak and comprehend English.

Materials

As in the Pretz et al. (2010) study, pictures from the International Affective Picture System were used to induce mood. The IAPS is a standardized database of pictures used to induce mood in a standardized setting. The pictures have been rated for both valence (i.e., mood) and arousal (i.e., level of excitement). They have been rated on a 9 point scale, with 1 representing unpleasant and 9 representing pleasant for valence and 1 representing calm and 9 representing excited for arousal. Because the Pretz et al. method did not indicate which exact pictures were used, pictures were chosen that had similar valence ratings. The pictures chosen for the positive condition have a mean valence rating of 7.59 ($SD = 1.49$) and an arousal rating of 4.95 ($SD = 2.37$) on 9 point scale. Unfortunately, the pictures cannot be included in the appendices due to the fact that I had to sign an agreement with the creators of the database that I

would not include the pictures in any print format; however, see Appendix F for the IAPS numbers and image ratings. As a general description, the positive pictures include images such as people smiling, families, couples, and babies. The negative pictures have a mean valence rating of 2.39 ($SD = 1.51$) and arousal rating of 5.60 ($SD = 2.20$). The negative images depicted themes such as abuse, accidents, and death. The neutral images have a mean valence rating of 5.07 ($SD = 1.35$) and arousal rating of 3.50 ($SD = 2.00$). The set included images of household items, people performing mundane activities, and manmade structures such as golfing and crossword puzzles.

The Positive And Negative Affect Schedule (PANAS) were used for the mood manipulation check (Watson, Clark, & Tellegen, 1988). As noted in the pilot study, the PANAS contains 10 positive mood words (e.g., alert) and 10 negative mood words (e.g., upset). Participants rated how they were feeling at the current moment on a scale of 1 to 5 (1 being not at all and 5 being extremely).

Although the Pretz et al (2010) study used both an artificial grammar learning task and the serial reaction time task, the current replication only included the artificial grammar task as it is most relevant to the current investigation. The artificial grammar task was duplicated as closely as possible, but the paper did omit some details; these were filled in based on methods used in other artificial grammar learning studies (e.g., Patterson et al., 2013). Twenty letter sequences generated from the Reber (1967) finite-state diagram were used during the presentation phase. The grammar test included a total of 50 letter sequences with 7 from the presentation phase, 19 letter sequences that were novel but were not included in the presentation phase, and 24 non-grammatical letter sequences. See Appendix E for the complete set of materials that was used in the artificial grammar test.

Procedure

Experiment 1 was conducted using Qualtrics (Qualtrics, Provo, UT); and after consenting, participants were asked to view pictures. If they were in the negative mood condition, they were given a warning that the pictures were graphic and reminded that they could withdraw from the study at any time. The pictures were automated and appeared on the computer screen for 5 s with 1.5 s blank screen between pictures, just like the Pretz et al. (2010) study. Immediately afterward, they completed the PANAS.

Following the PANAS, they began the artificial grammar learning task. Most artificial grammar studies (e.g., Patterson et al., 2013) do not instruct participant to direct their attention or memorize the stimuli; however, because the previous study (Pretz et al., 2010) explicitly instructed participants to memorize the sequences, participants in the current study were also asked to do this. Because the Pretz et al. (2010) study did not describe how long the letters were shown, Experiment 1 used display times similar to other related studies (e.g., Covas-Smith, 2011); specifically, the letter strings were shown for 4 seconds with a 1 second blank screen.

After viewing the sequences of letters, participants were made aware that the sequences they tried to memorize had an underlying pattern. They were then asked to make grammatical judgments by answering ‘yes’ with the mouse to sequences they believed were structured (i.e., consistent with the pattern) and answering ‘no’ with the mouse for the picture sequence being unstructured (i.e., inconsistent with the pattern). Participants were then thanked for their time, debriefed, and assigned credit.

Design and Analysis

To check whether the mood manipulation procedure was effective, the PANAS scores were submitted to a between-subjects Analysis of Variance (ANOVA). A separate ANOVA was run for Positive Affect and Negative Affect. Test scores on the grammar test were submitted to a between-subjects ANOVA with mood group (positive, negative, neutral) as the independent variable. If the results conform with the original study (Pretz et al., 2010), then the negative group will outperform both the positive and neutral groups. It was predicted that this trend would be found because there is no reason to believe that the Pretz et al., (2010) would not replicate.

Results

PANAS

The mean PANAS scores are presented in Figure 10. A between-subjects ANOVA indicated that the mood induction had a marginally significant effect on Positive Affect scores, $F(2, 111) = 2.763$, $MSE = 174.588$, $p = 0.067$, $\eta^2 = 0.047$, and a significant effect on the Negative Affect scores, $F(2, 111) = 63.425$, $MSE = 1620.500$, $p < .001$, $\eta^2 = 0.533$. A Tukey's Hones Significant Difference (HSD) post hoc test revealed that the positive and negative group were statistically significant from each other ($p < .001$, $SE = 1.160$) with the negative group reporting higher Negative Affect scores. The negative group also reported higher Negative Affect than the neutral group ($p < .001$, $SE = 1.160$). However, the positive and neutral groups were not statistically significant in their reported Negative Affect scores.

Grammar Test

Percent scores from the grammar test were averaged to create group means for each mood condition (negative, positive, neutral) and the means are presented in Figure 10 (also see Figure 11 for a boxplot). All groups scored above chance (i.e., 50%), $t(113) = 13.076, p < .001$. The group means were submitted to a one-way between-subjects ANOVA. For all analyses, an alpha level of 0.05 was used to determine statistical significance. The test indicated that overall, mood did have a significant effect on grammar test scores $F(2, 111) = 3.212, \text{MSE} = 0.024, p = 0.044, \eta^2 = .054$. Follow up t-tests were conducted to compare group differences and a Tukey's Honest Significant Difference (HSD) post hoc test revealed significant differences only between the negative group ($M = 61.110, SD = 7.289$) and the neutral group ($M = 58.020, SD = 81.800$), $p = 0.036$.

Signal detection analysis scores were computed to determine the ability of the participants to perceive the signals (i.e., sequences) from the background noise for both the correct items and the consistent items on the grammar test. As a reminder, the correct items are the sequences that were presented to the participants during the viewing phase and the consistent items are sequences that were not presented during the viewing phase but are consistent with the artificial grammar. Hit rate, miss rate, false alarm rate, correction rejection rate, sensitivity (d'), and criterion(c) were computed and are shown in Tables 1 and 2. All the signal detection analyses were submitted to a between-subjects ANOVA and revealed that hit rate and miss rate (which are complimentary values) was significant, $F(2, 111) = 4.051, \text{MS} = 0.164, p = 0.020$. A follow up Tukey HSD test indicated that the negative ($M = 0.688, SD = 0.169$) and neutral group ($M = 0.560, SD = 0.211$) were statistically different from each other, $p = 0.018$. The measure of sensitivity (d') was also significant, $F(2, 111) = 3.548, \text{MS} = 0.102, p = 0.032$, with negative (M

= 0.717, $SD = 0.557$) and neutral group ($M = 0.352$, $SD = 0.352$) again being statistically significant from each other, $p = 0.024$. There were no other statistical differences for the other three signal detection measures for consistent items and no differences for all six signal detection measures for the consistent items (all $p > 0.05$).

Discussion

The PANAS showed that the mood induction was successful. The accuracy data showed that those in the negative group outperformed those in the positive and neutral group, with the neutral group performing the worst. The signal detection analysis measure showed that negative participants had significantly more hits, misses, and sensitivity (d') for the correct items. There were no differences for consistent items between mood groups.

This pattern of results for Experiment 1 successfully replicated the trend from the Pretz et al. (2010) study, although the differences between mood groups were smaller here. In the current investigation, only the negative and neutral mood groups were significantly different from each other, but in their study they found all three groups to be significantly different from one another; however, they only reported their results with a covariate. A final point is that after the completion of Experiment 1 of this dissertation, it was discovered that the Pretz et al. (2010) study was based on an unpublished undergraduate thesis; the experiment description in this thesis was more detailed and revealed that participants saw the letter strings two times and had to type in the letter strings immediately after seeing them, which is not a typical artificial grammar learning procedure. Therefore, the method used in those studies encourages people to focus their attention and that could potentially benefit those negative mood participants who were already experiencing a narrowing of attention due to the mood induction procedure.

While these results are in line with Pretz et al. (2010), they are only partially in line with the affect-as-information hypothesis. As a reminder, the affect-as-information hypothesis posits that those in a negative mood have a narrower focus of attention and a better memory for details. In this sense the affect-as-information was supported because the negative group scored higher on the correct items that were presented during the viewing phase, suggesting that the negative mood could have improved their memory for the exact letter strings. At this point, it is unclear why the trends in Pretz et al. (2010) and Experiment 1 contradicted the pilot study. One possibility is that the results from the former are more driven by arousal than valence. After all, the positive and negative groups were not statistically different and both had higher levels of arousal than the neutral group. To examine this more closely, Experiment 2 included two positive mood groups: one with high arousal images and one with low arousal images.

CHAPTER 6
EXPERIMENT 2

Method

Participants

A total of 188 participants (47 per mood condition) were recruited from the subject pool at the University of Nevada, Las Vegas; none of them participated in the earlier experiments. Participants were issued research credit for their psychology course. All participants were able to fluently speak and comprehend English and had normal or corrected vision.

Materials and Procedures

Like the pilot, Experiment 2 had a mood induction phase that also served as the learning phase. This differed from Experiment 1 where the mood induction was separate. Also, in Experiment 2 participants were presented and tested with pictures instead of letters. All of the tasks were completed on a PC using Qualtrics (Qualtrics, Provo, UT). Mood condition and training condition were counterbalanced across participants. Additionally, four sets of pictures were created for each mood condition and these sets were counter-balanced across participants. The IAPS numbers for all the images used are listed in Appendix H. The participants selected for the training phase were asked to view picture sequences that were positive-high arousal, positive-low arousal, negative, or neutral in valence for 5 seconds with 1 second pauses between the sequences. Unlike Experiment 1, participants were not instructed to direct their attention or memorize the stimuli; they were not given any feedback. However, for ethical reasons, participants in all the training groups were told that some of the pictures may upset them and

reminded that they can quit the experiment at any time. It is unlikely that the participants in the positive and neutral groups would find the pictures upsetting but the warning was given to all groups in case the warning had a priming effect (No participants requested to quit.).

As in the pilot experiment, the order of the pictures was determined using a finite state algorithm. Twenty sequences were presented 10 times leading to a presentation phase of approximately 30 minutes. The sequences were presented several times because increasing training typically produces better performance that is significantly greater than chance (Patterson et al., 2013).

After the training phase, participants immediately completed the PANAS to ensure that the mood manipulation procedure was effective. They were then informed that the pictures they just viewed were following an underlying pattern and completed a yes / no recognition test on the computer where they selected 'yes' for the picture sequence being structured (i.e., consistent with the pattern) and 'no' for the picture sequence being unstructured (i.e., inconsistent with the pattern). The test consisted of 60 sequences; 20 that were previously presented, 20 sequences that were novel but consistent with the finite-state grammar, and 20 random sequences (i.e., foils). The order of the sequences was random. A separate group of participants were asked to make the distinction between the structured and unstructured sequences in a similar manner as the training groups.

Participants then completed the Analysis-Holism Scale (AHS) (Choi, Koo, & Choi, 2007). The AHS was used to examine whether the mood manipulation influences the way people perceive wholes versus parts. Specifically, the AHS is used to look at individual differences in regard to analytic versus holistic thinking. It includes 24 questions with a higher score being

associated with a preference for holistic thinking and lower scores associated with more analytic thinking. Participants rated statements such as, “Everything in the world is intertwined in a causal relationship,” on a 7 point scale (1= strongly disagree, 7 = strongly agree). Participants responded to each item by typing in the corresponding number for their response on a standard keyboard. See Appendix G for the full questionnaire. The participants were then debriefed and given credit for their participation.

Design and Analyses

The primary dependent variable of interest is the percent correct for the recognition test. The mean scores were submitted to a 4 (mood: positive-high arousal, positive-low arousal, negative, or neutral) between-subjects ANOVA. Additionally, d' and bias scores were computed for training conditions to examine how the mood manipulation impacted the sensitivity and tendency to respond ‘yes’. It was expected that the results would mirror the pilot with a main effect of mood, with the positive group performing the best on the test. This would be consistent with the affect-as-information hypothesis. Specifically, those in a positive mood have a broadening of attention, allowing them to form more connections. It was also expected that all the mood groups would perform above chance. With regards to the AHS, it was predicted that those in a positive mood would score more holistic and those in a negative mood would score more analytic. This would also be consistent with the affect-as-information hypothesis.

Results

PANAS

The baseline mean Positive Affect score was 31.872 ($SD = 7.833$) and the baseline Negative Affect score was 15.181 ($SD = 5.655$). These are in line with normative momentary ratings of 29.7 ($SD = 7.9$) Positive Affect and 14.8 ($SD = 5.4$) Negative Affect as reported by Watson et al. (1988). The individual PANAS group means for pre and post mood induction are reported in Table 3. A paired-samples t -test was conducted to compare baseline scores to post mood induction scores. There was a significant decrease in Positive Affect scores from pre to post mood induction, $t(187) = 7.587$, $SE = .5553$, $p < 0.001$ for all groups. However, there were no significant differences for the Negative Affect scores.

Grammar Test

Percent scores from the grammar test were averaged to create group means for each mood condition (negative, neutral, positive-high arousal, positive-low arousal) and the means are presented in Figure 12 (also see Figure 13 for a boxplot). To determine whether training (i.e., the viewing phase) increased performance over chance (i.e., 50 %), a t -test was conducted comparing grammar test scores to chance performance. The t -test indicated that performance was above chance, $t(188) = 16.375$, $p < .001$. To ensure that the pattern was not salient enough to learn without the presentation phase, a test-only group of participants was examined; as expected, they did not score above chance, $t(75) = -1.359$, $p = 0.178$.

As in Experiment 1, the group means were submitted to a one-way between-subjects ANOVA. For all analyses, an alpha level of 0.05 was used to determine statistical significance.

The test indicated that overall, mood did not have a significant effect on grammar test scores, $F(3, 184) = 1.251$, $MSE = 0.013$, $p = 0.293$, $\eta^2 = 0.020$.

As in Experiment 1, hit rate, miss rate, false alarm rate, correction rejection rate, sensitivity (d'), and criterion(c) were computed and are shown in Tables 4 and 5. For the correct items, there were no differences for all six signal detection measures, as revealed by between-subjects ANOVAs (all $p > 0.05$). For consistent items, there was a marginal significant difference for sensitivity (d') scores, ($F(3, 184) = 2.353$, $MS = 0.754$, $p = 0.074$) with the positive-high arousal condition having the highest sensitivity, followed by the negative condition, then positive–low arousal, and the neutral group was the least sensitive.

AHS

Group means were computed for the four subdomains of the Analysis-Holism Scale and were submitted to a between subjects repeated ANOVA. There was a main effect of Analysis-Holism subdomain, $F(3, 184) = 19.058$, $p < 0.001$, $\eta_p^2 = 0.239$, indicating that mean scores on the four different subscales were statistically significant from one another. There was not a significant main effect of mood, $F(3, 184) = 1.018$, $MSE = 37.902$, $p = 0.386$, $\eta_p^2 = 0.989$. Finally, the interaction of AHS subdomains and mood was also not significant, $F(9, 184) = 1.623$, $MSE = 46.612$, $p = 0.105$, $\eta_p^2 = 0.026$.

Discussion

Experiment 2 investigated the possibility that mood inducing pictures presented in the artificial grammar paradigm would influence performance. Specifically, it was predicted that a positive-low arousal mood would result in the best performance which would be consistent with

the affect-as-information hypothesis. However, this hypothesis was not really supported because while the positive-low arousal group had the highest performance, the difference was not significant. This could be due to the long viewing phase making participants less positive about the experiment. That is, they viewed the same five pictures that were embedded in 20 sequences that were each presented 10 times. This lengthy process may have led them to find the task to be boring, which could have reduced their focus on the materials in general. In fact, participants' Positive Affect score decreased for all mood groups. Based on previous studies (Patterson et al., 2013), a long viewing phase is necessary to ensure that participants are learning the underlying pattern; but, as described above, a longer viewing phase can have a potential cost. There were also no significant mood differences on the AHS. This could be due to the AHS tapping into beliefs that may not be as transient as mood; thus, the mood induction procedure was not enough to change a person's overall cognitive style and way of viewing the world. The significant difference between the subdomains replicated previous research that found each subdomain distinct (Choi, Koo, & Choi, 2007).

To continue exploring different aspects of implicit learning, Experiment 3 investigated whether mood produces differences in implicit learning when a different picture is used to represent distinct categories. It was predicted that the positive-low arousal group would outperform the other groups and the differences would be more salient than in Experiment 2 due to larger variety of pictures hopefully being more pleasant to look at in the positive mood groups (i.e., not as repetitive, so therefore not as boring). Also, because a positive mood enhances the gist or big picture, it was predicted that the design of Experiment 3 would be more beneficial for the positive-low arousal group, leading to an outcome that would be consistent with the affect-as-information hypothesis. In other words, because all groups would hopefully not be as bored,

the positive-low arousal group would retain the wider focus of attention associated with being in a positive mood.

CHAPTER 7
EXPERIMENT 3

Method

Participants

A total of 200 participants were recruited from the subject pool at the University of Nevada, Las Vegas to place 50 participants per condition. Participants were issued research credit for their psychology course. All participants were able to fluently speak and comprehend English and had normal or corrected vision. None of these individuals participated in Experiment 1 or 2.

Materials and Procedure

. The materials and procedure for Experiment 3 were identical to Experiment 2 except for two changes. The first change was that there was not a test-only group in Experiment 3 because the same artificial grammar was used in Experiment 2 and did not yield above chance scores for the non-training group. The other change was that, instead of always using the same picture to represent a letter in the diagram (e.g., T for baby), a different picture was shown both during the presentation phase and during the testing phase. See Figures 14 to 17 for an example from every mood condition. Due to the IAPS not containing enough pictures, new pictures were found on the internet by the experimenter and were rated by a different group of participants prior to Experiment 3 to supplement the picture database. Pictures that had a Cronbach's alpha reliability rating of 0.80 and up and mean valence and arousal ratings, similar to the IAPS images used in Experiment 2, were selected. See Table 6 for valence and arousal ratings.

Design and Analyses

As in Experiment 2, the primary dependent variable of interest was the percent correct of the recognition responses made by the participants. The mean scores were submitted to between-subjects ANOVA (positive-high arousal, positive-low arousal, negative, and neutral). Additionally, d' and bias scores were computed for training conditions to examine how the mood manipulation impacted the sensitivity and tendency to respond 'yes'. It was expected that there would be a main effect of mood, with the positive-low arousal group performing the best on the test. This result would be consistent with the affect-as-information hypothesis with a positive mood broadening attention, thus leading to forming more relations between the categories. The positive-high arousal and neutral groups were predicted to have scores significantly different than the negative mood group.

Results

PANAS

The baseline mean Positive Affect score was 30.525 ($SD = 8.091$) and the baseline Negative Affect score was 15.770 ($SD = 5.967$). These scores were similar to the baseline scores in Experiment 2 and were also in line with normative momentary ratings of 29.7 ($SD = 7.9$) Positive Affect and 14.8 ($SD = 5.4$) Negative Affect as reported by Watson et al. (1988). The individual PANAS group means for pre and post mood induction are reported in Table 7. A paired-samples t -test was conducted to compare baseline scores to post mood induction scores. There was a significant decrease in Positive Affect scores from pre to post mood induction, $t(199) = 15.284$, $SE = .602$, $p < 0.001$ for all groups. However, there were no significant differences for the Negative Affect scores.

Grammar Test

As in Experiment 1 and 2, the group means were submitted to a one-way between-subjects ANOVA. For all analyses, an alpha level of 0.05 was used to determine statistical significance. The test indicated that overall, mood did not have a significant effect on grammar test scores $F(3, 196) = 1.907$, $MSE = 0.078$, $p = 0.130$, $\eta^2 = 0.028$ (see Figures 18 and 19 for means and spread). However, an independent t -test was conducted to compare the highest scoring group (negative) to the lowest (positive-high arousal) and found that the scores were marginally significantly different, $t(98) = 1.953$, $SE = 0.020$, $p = 0.054$.

As in Experiment 1 and 2, hit rate, miss rate, false alarm rate, correction rejection rate, sensitivity (d'), and criterion (c) were computed and are shown in Tables 8 and 9. For the correct and consistent items, there were no differences for all six signal detection measures, as revealed by between-subjects ANOVAs (all p 's > 0.05).

AHS

As in Experiment 2, group means were computed for the four subdomains of the Analysis-Holism Scale and were submitted to a between subjects repeated ANOVA. There was a main effect of Analysis-Holism subdomain, $F(3, 196) = 26.181$, $p < 0.001$, $\eta_p^2 = 0.118$, indicating that mean scores on the four different subscales were statistically significant from one another. There was not a significant main effect of mood, $F(3, 196) = 0.868$, $MSE = 34.035$, $p = 0.459$, $\eta_p^2 = 0.989$. Finally, the interaction of AHS subdomains and mood was also not significant, $F(3, 196) = 0.389$, $MSE = 9.789$, $p = 0.761$, $\eta_p^2 = 0.006$.

Discussion

Experiment 3 investigated the possibility that mood inducing images that represented a category would influence implicit learning. It was expected that the same trend of results from Experiment 2 would be magnified, but this hypothesis was not supported. The negative and positive-high arousal groups were marginally significant from each other, but no other differences were observed. In essence, because the negative group was assumed to be high arousal, the two high arousal groups were the only groups that differed. However, arousal studies have shown that arousal can be beneficial up until a point but then becomes detrimental (Lupien et al., 1997; Yerkes & Dodson, 1908). Therefore, it is possible that the level of arousal in the negative mood condition was beneficial but the level and / or type of arousal in the positive-high arousal condition was detrimental.

CHAPTER 8

GENERAL DISCUSSION

Four experiments were conducted to examine the relationship between mood and implicit learning. A pilot experiment was used to make sure that this was an area worth pursuing dissertation work. It was found that positive mood participants outperformed negative mood participants when the mood induction task was also the implicit learning phase. The positive mood condition performed better with both a simple and complex grammar. However, the results contradicted the only prior study that had investigated artificial grammar learning and mood (Pretz et al., 2010).

The goal of Experiment 1 was to replicate the Pretz et al. (2010) study, which showed that those in a negative mood performed better on an artificial grammar learning task. Participants saw mood inducing images before being presented with letter sequences to memorize, and were then given a grammar test. In contrast to the pilot experiment, the Experiment 1 results replicated the basic trend that was observed by Pretz et al., but the effect was not as large (as is common in many replication studies). The results support the fact that the Pretz et al. (2010) findings were not an anomaly and it appears that when participants are given a separate mood test and then an artificial grammar task, those in a negative mood have a slight advantage.

Experiment 2 was an expansion of the pilot study. The procedure was very similar except that the images used came from the IAPS; also, two additional mood groups were added (positive-high arousal and neutral). The Experiment 2 results showed the same trend as the pilot experiment, with the positive-low arousal group outperforming the negative mood group, but this

pattern in Experiment 2 was not statistically significant. It is unclear why the positive-low arousal group did not score as high as the positive group in the pilot experiment, but perhaps the mixed arousal pictures in the pilot lead to higher scores. However, the lack of significance could also be due to type II error or lack of power.

One question that remains is why Experiment 2 produced different results than Experiment 1. One possibility is that the same pictures being shown repeatedly could make the stimuli less surprising, which is known to decrease memory performance (e.g., Marchewka et al., 2016). Another possibility is that the integral nature of the task, as was used in Experiment 2, impacts implicit learning differently. As a reminder, integral tasks refers to when the stimuli to be learned or remembered is mood inducing, whereas, when the stimuli are unrelated, it is referred to as incidental which is more common in mood research (e.g., Blanchette & Richards, 2010) and what was used in Experiment 1 (Experiment 3 was integral but not as integral as Experiment 2).

Experiment 3 examined the effect of mood on implicit learning when the artificial grammar task was based on categories. The design of this experiment has the most ecological validity as it is more common to encounter different instances of mood inducing stimuli in our environments. The Experiment 3 results showed that all groups learned the underlying grammar; however, the mood differences were somewhat small or not present. That is, the only groups that were marginally significant were the negative (high arousal) and positive-high arousal groups. One possible explanation is that the positive-high arousal group viewed images that were the most approach motivated, meaning that they may have had the strongest urge to approach an object (e.g., Gable & Harmon-Jones, 2008). As discussed in the introduction, approached motivated stimuli elicit an action (e.g., a picture of cupcakes making someone want to get ice

cream), which is known to reduce the breadth of focus (e.g., Gable & Harmon-Jones, 2008) as opposed to stimuli that are not as approach motivated (e.g., pictures of cute puppies). This is the first study (to my knowledge) to show that category learning can be achieved with an artificial grammar learning paradigm; it was demonstrated with a statistical learning paradigm (Brady & Olivia, 2008) but, as discussed in the introduction, statistical learning is based on a much simpler algorithm.

Affect-As-Information Hypothesis

Given the pilot experiment results and the numerous studies (for a review, see Clore & Huntsinger, 2007) supporting the affect-as-information hypothesis, I had predicted for Experiments 1, 2, and 3 that those in a positive mood would perform better on the artificial grammar learning test. However, all three experiments produced results that were not consistent with the affect-as-information hypothesis. Experiment 1 did not necessarily contradict the hypothesis because it makes predictions pertaining to differences between positive versus negative mood, and the significant effect in Experiment 1 was driven by differences between the negative and neutral group. Experiment 2 did not find differences so it is neither supporting nor aligning to the affect-as-information hypothesis. However, Experiment 3 somewhat conflicts with the affect-as-information hypothesis with the negative group performing the best and the positive high arousal group performing the worst.

These findings lead to the question as whether the affect-as-information hypothesis applies to all of the implicit learning scenarios explored in this dissertation. One possibility is that, because implicit learning is different than explicit learning, mood does not affect it in the same way. For instance, it is debated (e.g., Perruchet & Pacteau, 1990) whether artificial

grammar learning relies more on learning small chunks or learning more broad rules.

Experiments 1 and 3 suggest that implicit learning is more dependent on learning smaller chunks, thus, giving those in a negative mood an advantage. Therefore, the affect-as-information hypothesis may not be incorrect, but it might not apply to non-declarative learning processes. In a similar vein, perhaps mood in general does not have that much bearing on implicit processes given the null results of Experiment 2 and the small effect sizes in the other experiments. This would also be in line with those who have posited that implicit learning is more resistant to individual differences due to being an evolutionary old ability (e.g., Reber, 1993).

The inclusion of arousal could also contribute to the results not being in perfect alignment with the affect-as-information hypothesis. Many studies only look at valence, and arousal is not studied as much despite it being important to how events are perceived and to other types of cognitive processing (e.g., Ochsner, 2000). Some studies have found that arousal is only beneficial to memory up to a certain point and then it becomes detrimental (Lupien et al., 1997; Yerkes & Dodson, 1908). This is consistent with what was found in Experiment 3 and possibly Experiment 1.

CHAPTER 9

LIMITATIONS AND FUTURE DIRECTIONS

One limitation in these experiments was that the mood induction / viewing phase was rather long at approximately 30 minutes. Mood inductions are very transient (Westermann et al., 1996) so it is possible that it wore off in some cases. There is some evidence for this, because comparisons of the post to pre PANAS for the positive scores showed smaller effects for the former. This was a trade-off, however, as a longer viewing phase was administered to ensure that participants could learn the pattern at levels well above chance. Future studies can manipulate the number of learning trials presented to achieve a better mood / learning balance.

Another possible limitation is attention allocation. Attention is a known factor that affects implicit learning (e.g., Patterson et al., 2013). In the case of this dissertation, the learning task was also the mood induction, which made attention to the learning materials doubly critical. It is possible that certain mood groups could have allocated varying amounts of attention. For example, perhaps the slightly erotic images in Experiment 3 made participants uncomfortable and not as likely to focus their attention. Bennion, Ford, Murray, and Kensinger (2013) recommend using eye gaze as a covariate to account for attention; future studies exploring implicit learning in relation to mood and arousal could use eye tracking to ensure that all groups are allocating equal amounts of attention.

Because it remains unclear as to whether a more broad or narrow focus benefits implicit learning, those processes could be more directly studied with an artificial grammar task that contains letters that are composed of smaller and different letters, as was employed in the Kiyokawa et al. (2012) study that examined cultural differences and implicit learning. Of course,

the mood manipulation would have to be separate as in Experiment 1, which could be another variable that influences the relationship between mood and implicit learning.

In my opinion, future experiments should continue to investigate the complicated relationship between mood, arousal, and implicit learning as the experiments in this dissertation just scratched the surface of this issue. In addition to incorporating factors that could influence mood (as mentioned above), it would also be useful to examine some of the factors that influence implicit learning such as transfer. Pictures could be presented for the viewing phase and then participants could be tested on only letters at test; however, it is possible because the testing stimuli would not contain mood inducing stimuli, that mood could wear off. To address this possibility, the targeted mood state could be emphasized with music or stories presented aurally during the testing phase.

As mentioned previously, attention can influence implicit learning and only a small amount of attention is required for learning to occur (e.g., Saffran et al., 1997). Because large amounts of attention are not required for implicit learning, future studies can examine how mood interacts with divided attention. Although, it should be kept in mind that making a task more difficult is known to make a positive mood group less positive (e.g., Braverman, 2005). In this case, with a relatively easy and somewhat mundane task of viewing pictures for several minutes, maybe an additional task such as articulatory suppression would actually make the task more appealing.

This dissertation may be the first step in having real world implications for those who work in jobs involving implicit learning in emotional situations. For example, military analysts often work in high pressure situations where they are watching surveillance feeds with the goal

to identify suspicious activities. Therefore, an analyst has to be proficient at picking up on the regularities in their environment so they can detect the anomalies (e.g., an IED hidden under clothing). Experiment 3 most resembles real life situations because analysts are more likely to see different objects from the same categories, rather than repetitions of the exact same objects. The results from Experiment 3 would suggest that a more negative or neutral mood state would be beneficial to detecting anomalies. This will of course have to be corroborated with further studies, but if this finding holds up, it will be useful for analysts to know that witnessing harrowing sights such as victims of war will not impair their ability to perform their job.

As stated earlier, the patterns observed across the three main experiments did not fit perfectly with the affect-as-information hypothesis. Any, or all, of the possibilities described above could be explored to gain a better understanding of how mood and arousal influence implicit learning. These possibilities should be explored so that the complex relationship can be more fully understood. Once this is achieved, the result can be applied be shared with those who have to rely on implicit processes at their jobs, such as military analysts.

CHAPTER 11

CONCLUSION

In summary, three experiments, plus a pilot experiment, examined mood and implicit learning. The mood groups in all four experiments performed at above chance levels on the grammar tests. Unfortunately, like the previous studies conducted (e.g., Bertels et al., 2013; Pretz et al., 2010; Shang et al., 2013), the pattern of mood was not clear cut. The affect-as-information hypothesis was not observed, as there was a slight benefit for those in a negative mood in two of the experiments. However, the experiments did show that people were able to learn implicitly when the stimuli were mood inducing. Moreover, people were also able to implicitly learn categories. This dissertation added to the few studies (Bertels et al., 2013; Braverman, 2005; Pretz et al., 2010; Rathus et al, 1994; Shang et al., 2013) that have investigated the relationship between mood and implicit learning. The findings suggest that mood impacts implicit learning differently than explicit learning. It is recommended that the differences between implicit and explicit learning, and how both mood and arousal influences both types of learning, should be continued to be investigated in future research.

APPENDIX A: FIGURES

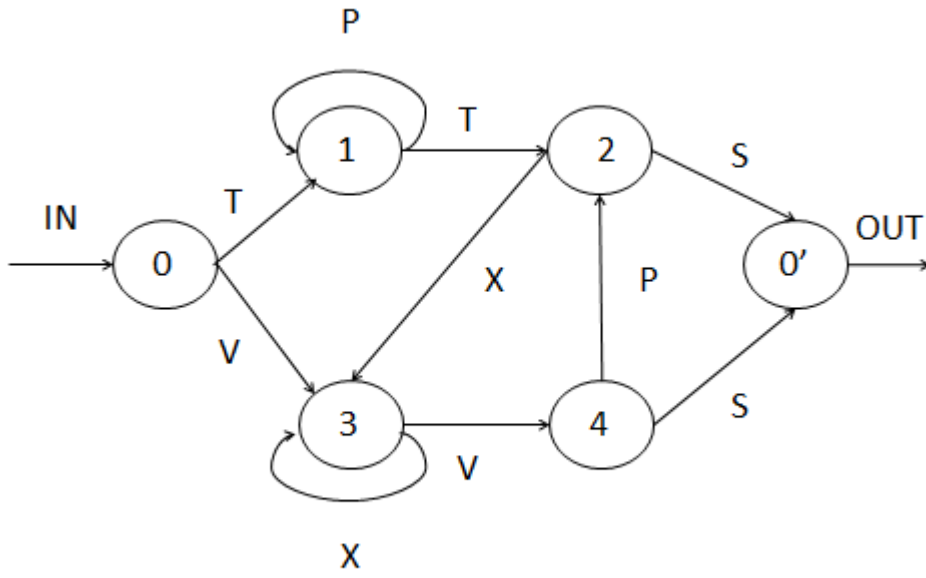


Figure 1. Transition diagram adapted from Reber (1967).

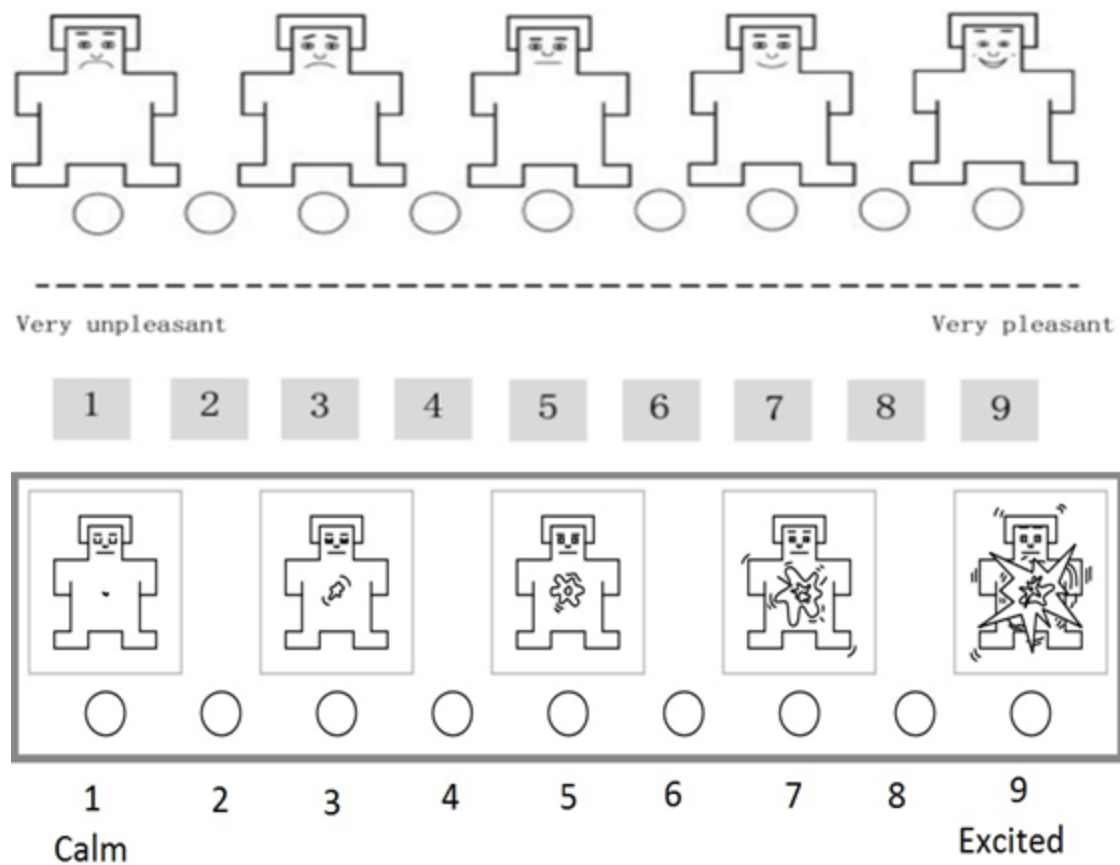


Figure 2. Self-Assessment Manikin adapted from Lang (1980).

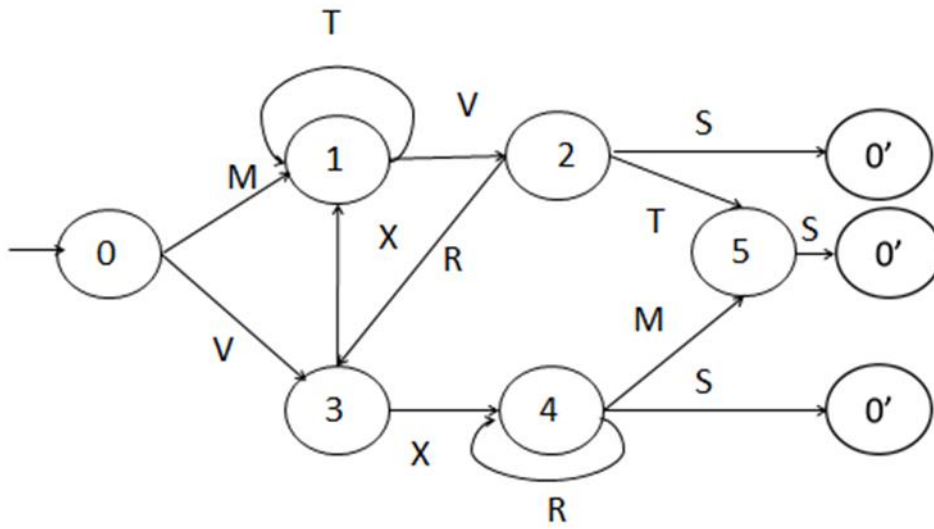


Figure 3. Modified Reber and Allen (1978) state diagram used to generate the complex grammar in the pilot experiment.

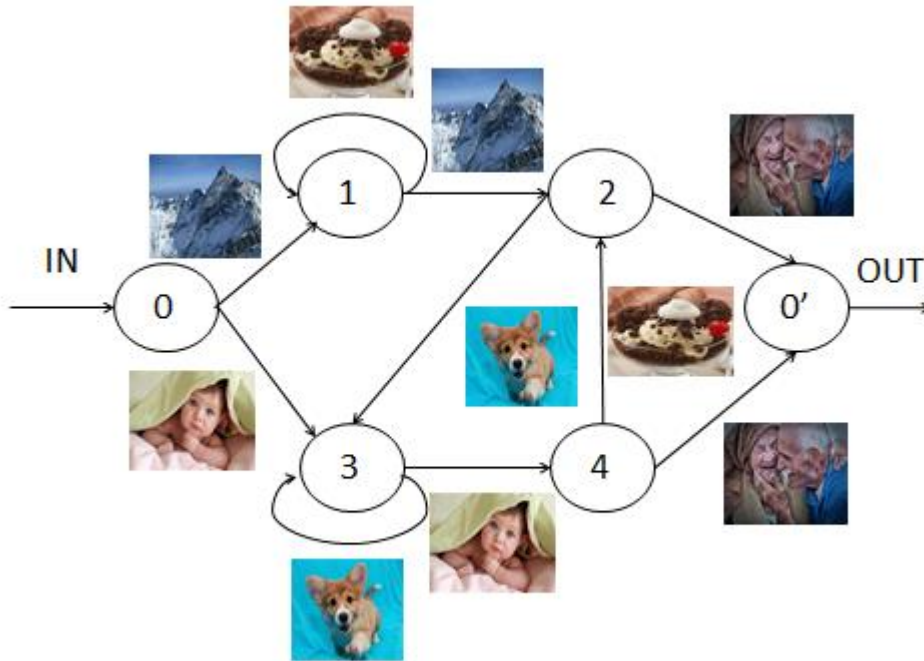


Figure 4. Positive condition for the simple grammar in the pilot study.

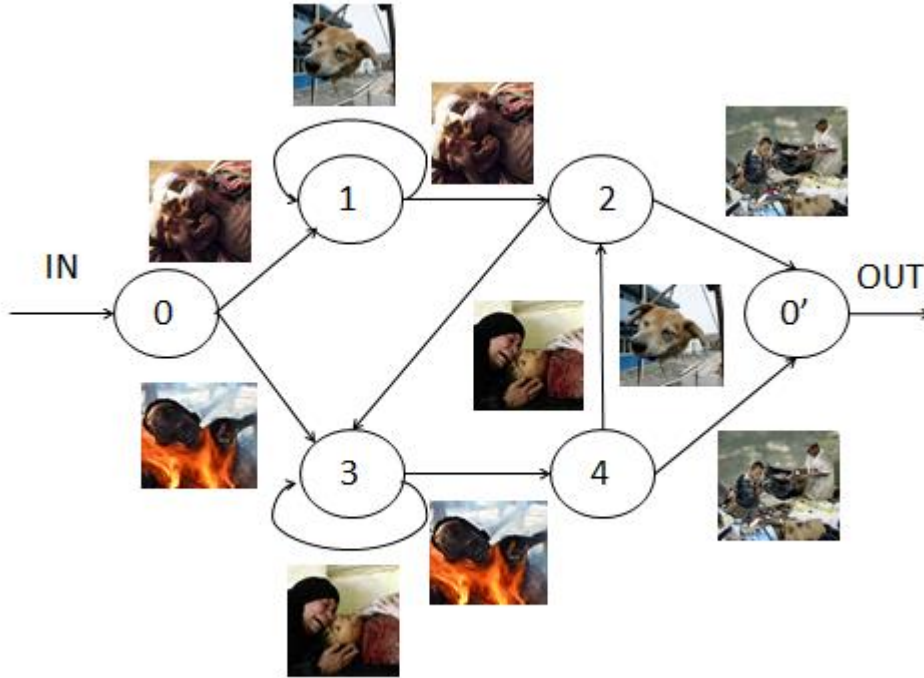


Figure 5. Negative condition for the simple grammar in pilot study.

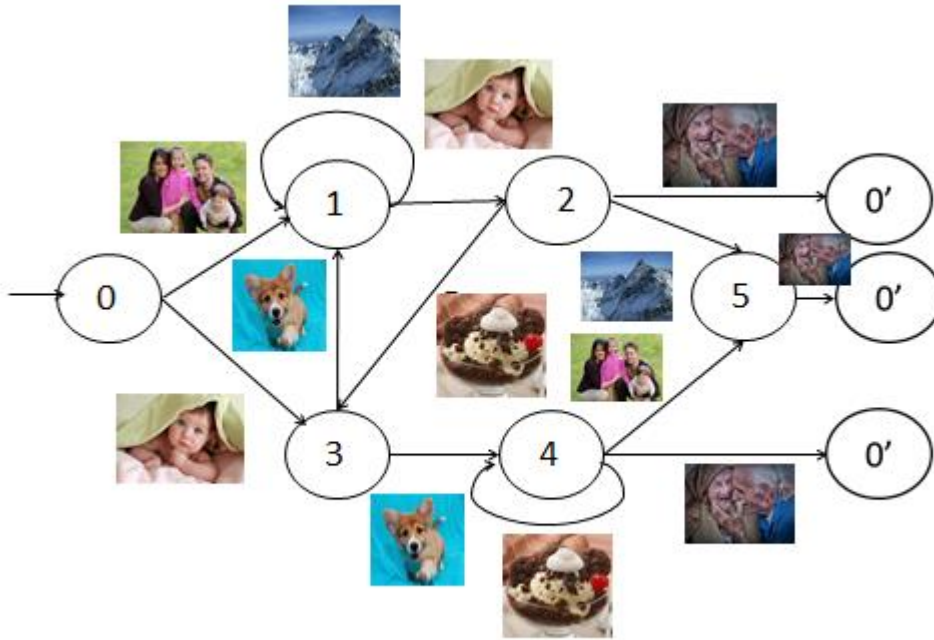


Figure 6. State diagram used to generate the complex pictures sequences for the positive mood condition in the pilot study.

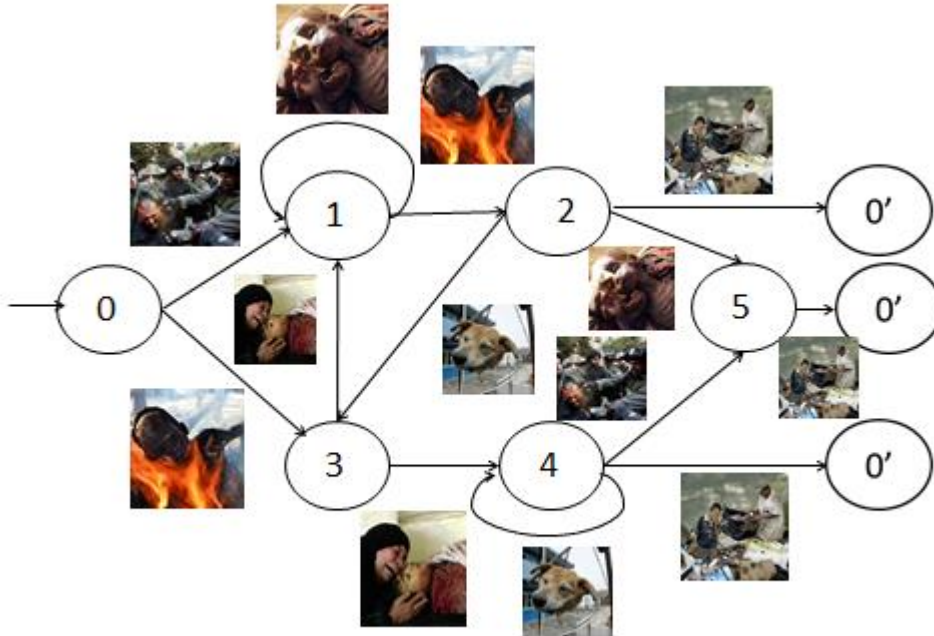


Figure 7. State diagram used to generate the complex pictures sequences for the negative mood condition in the pilot study.

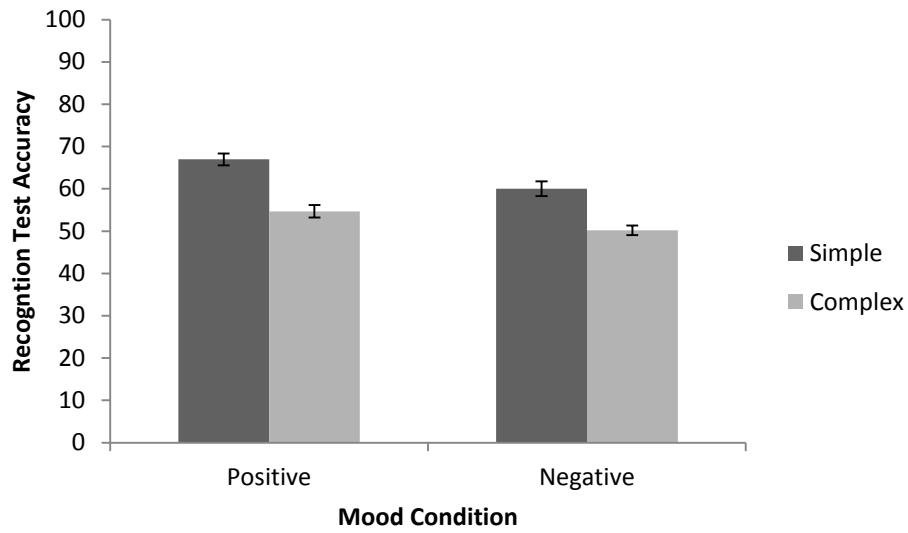


Figure 8. Mean accuracy scores for the positive and negative mood groups with the simple and complex grammars in the pilot experiment. The error bars reflect standard error.

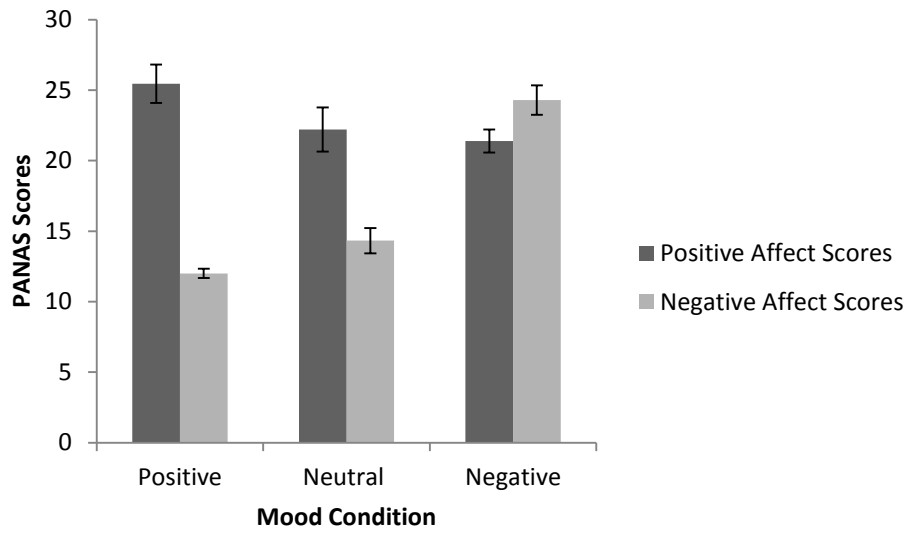


Figure 9. PANAS graph for Experiment 1. PANAS were collected after the mood induction. The error bars reflect standard error.

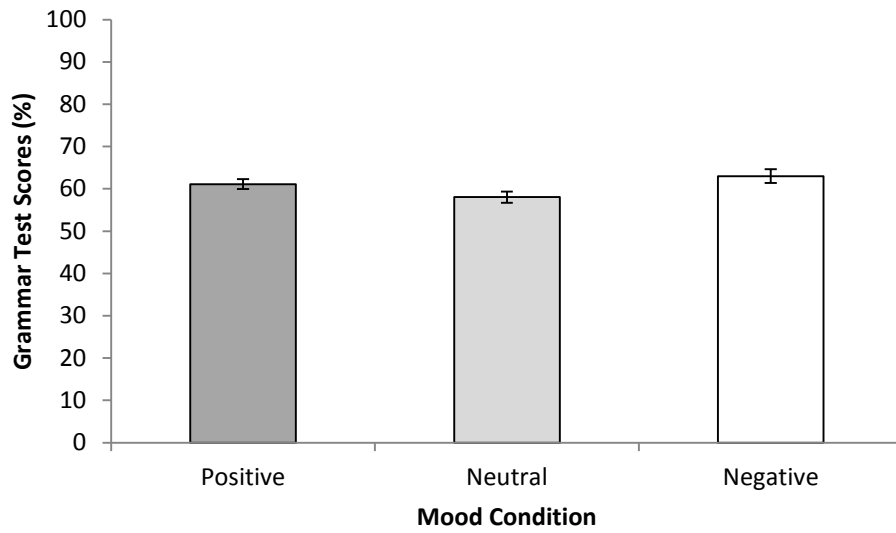


Figure 10. Mean accuracy scores for the different mood groups on the grammar test in Experiment 1. The error bars reflect standard error.

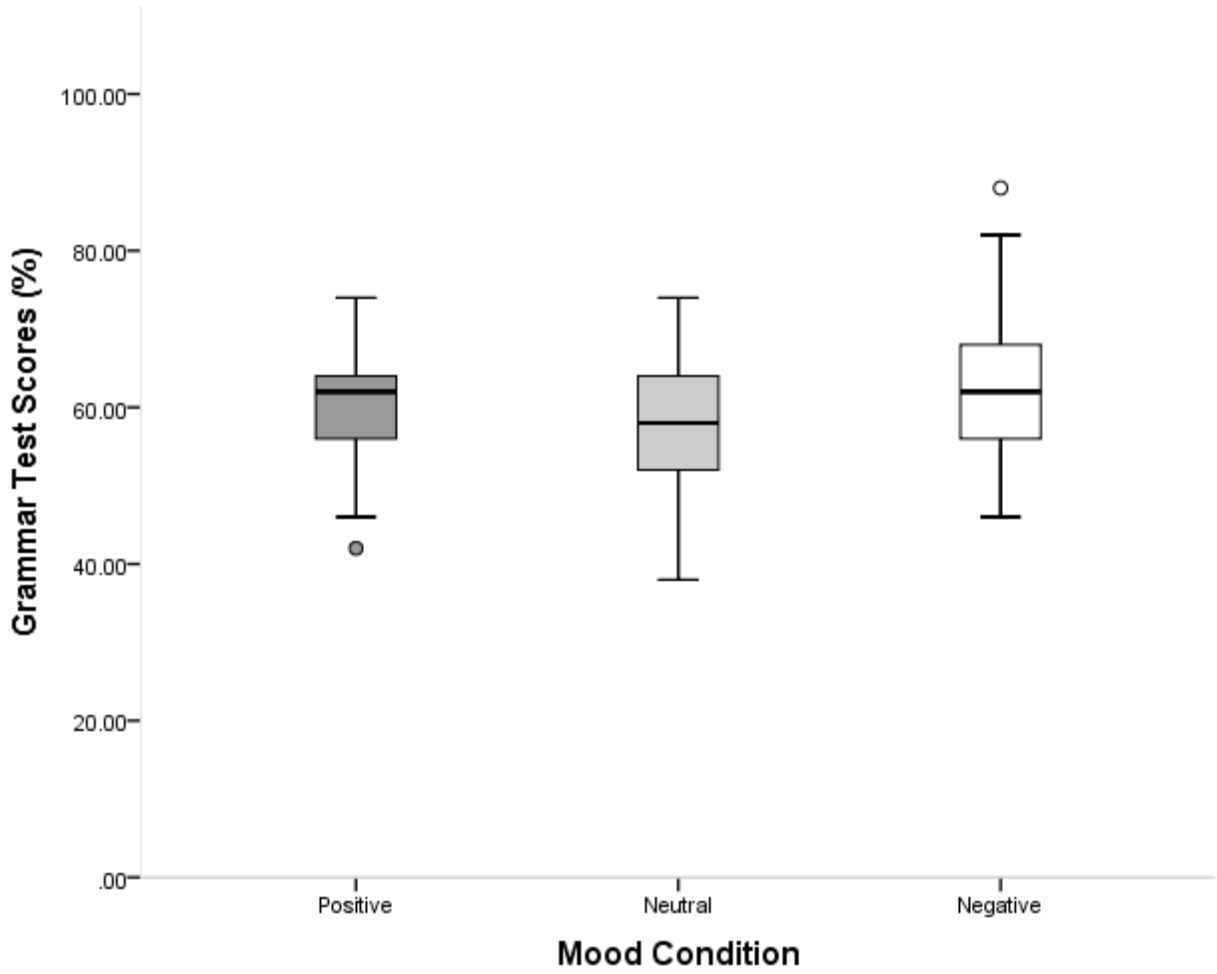


Figure 11. Boxplots of the accuracy data for Experiment 1.

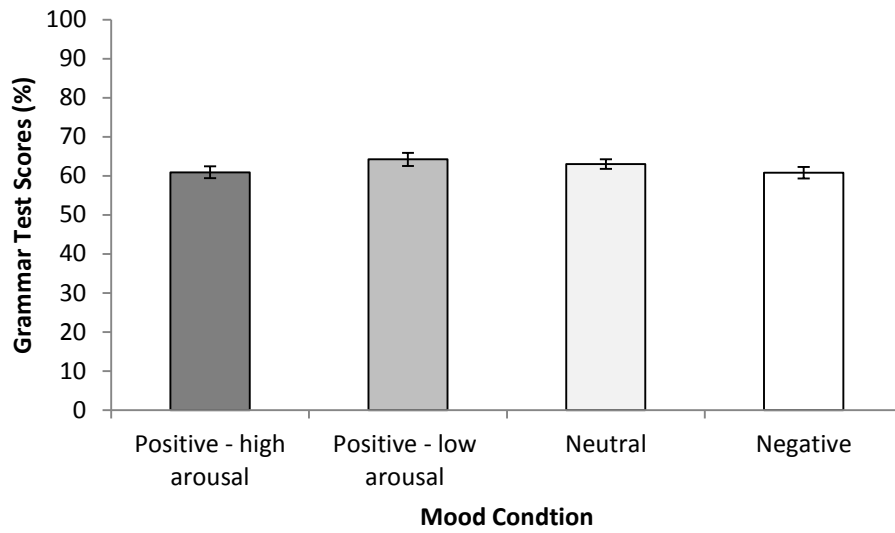


Figure 12. Mean accuracy scores for the different mood groups on the grammar test in Experiment 2. The error bars reflect standard error.

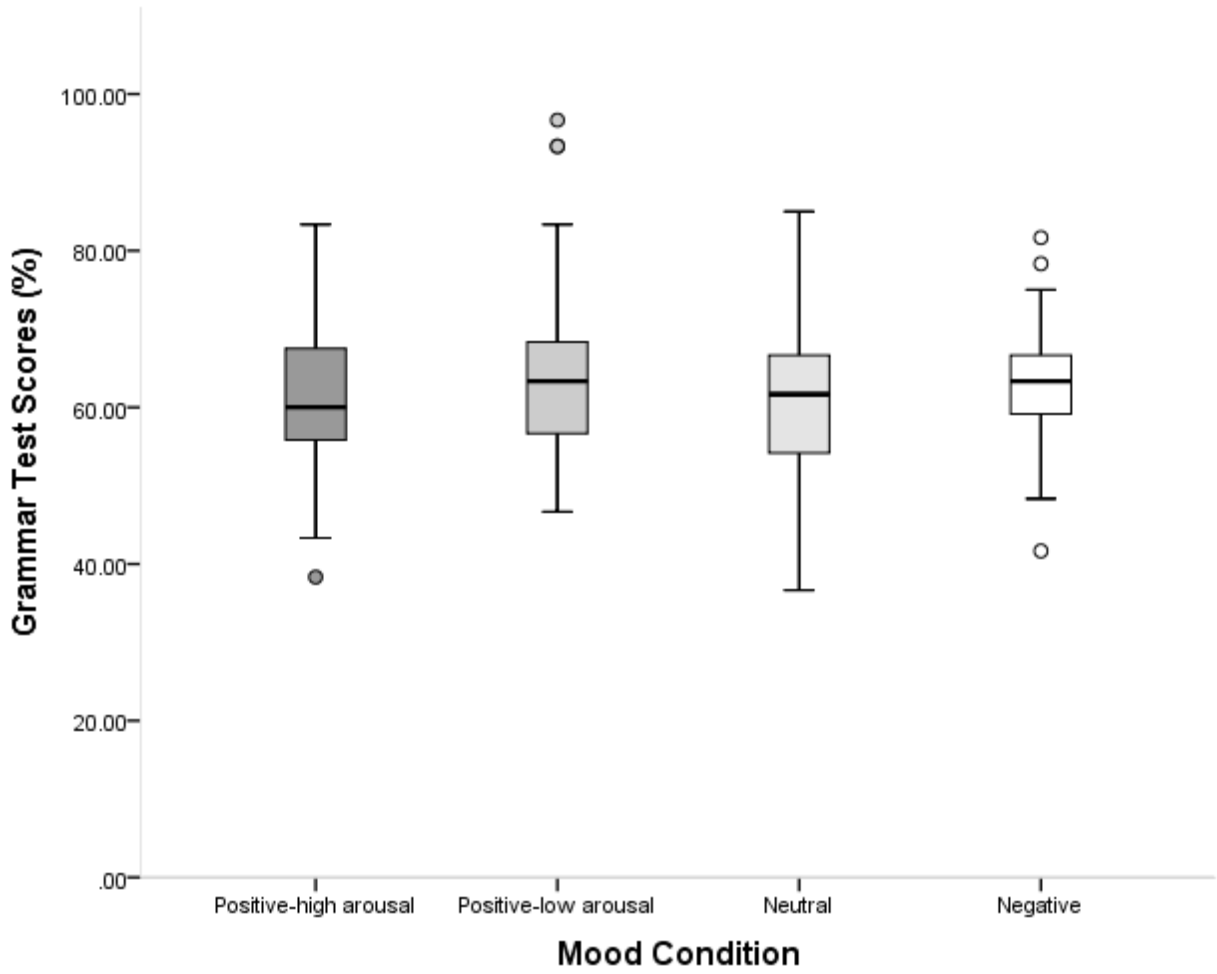


Figure 13. Boxplots for the accuracy data in Experiment 2.

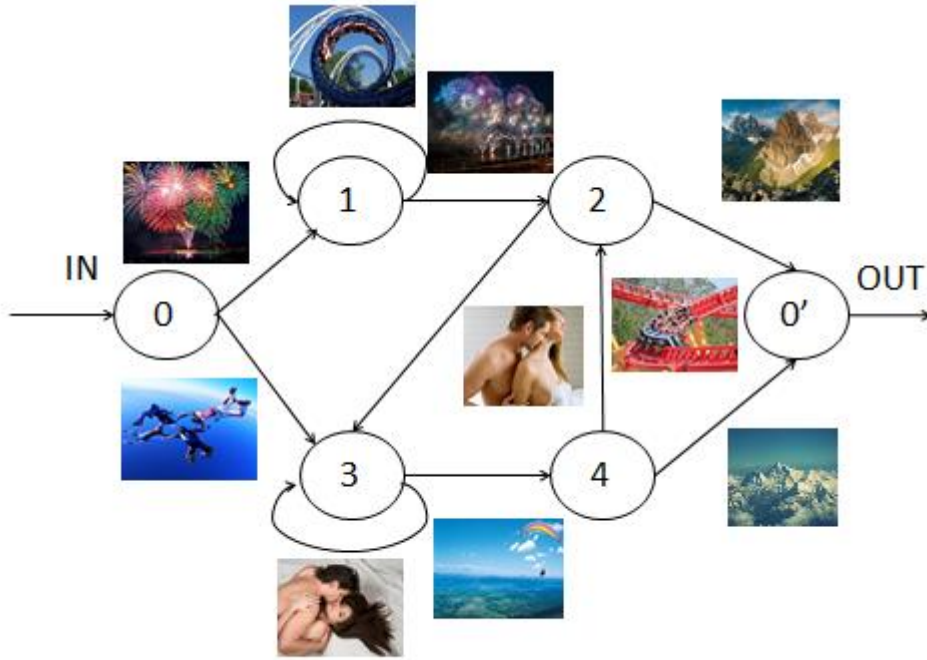


Figure 14. State diagram example for the positive-high arousal condition in Experiment 3.

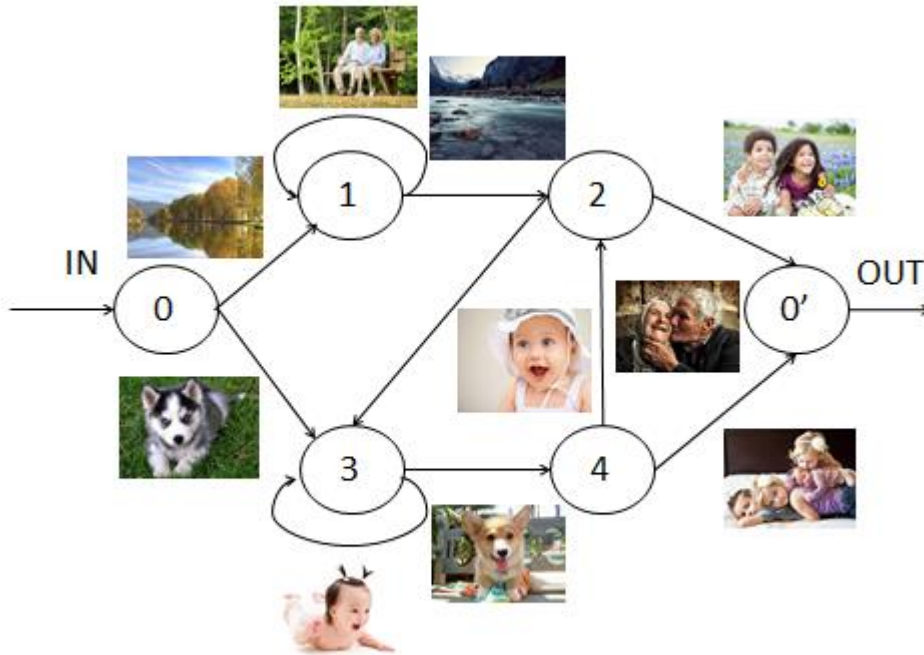


Figure 15. State diagram example for the positive-low arousal condition in Experiment 3.

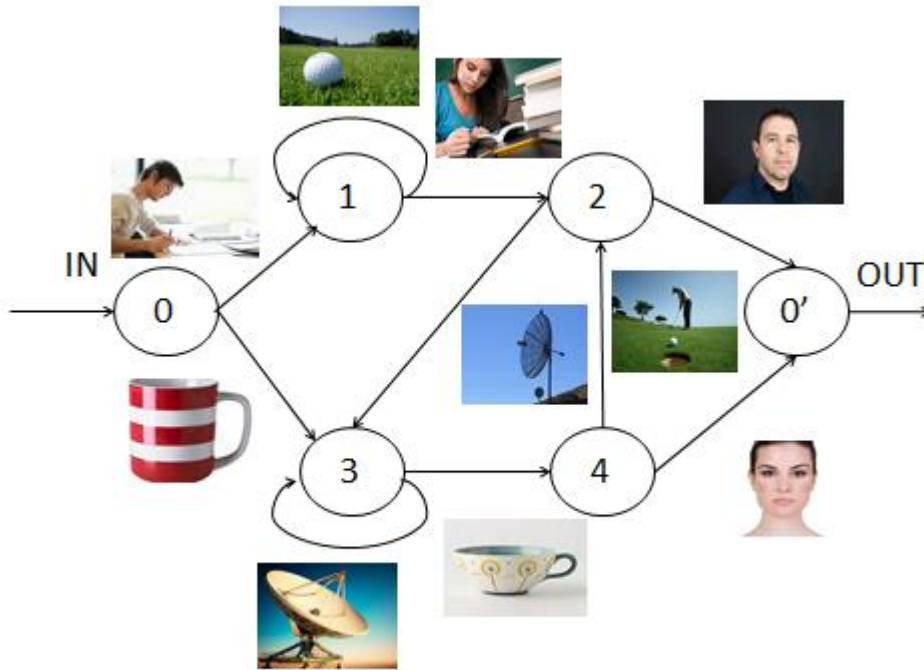


Figure 16. State diagram example for the negative condition in Experiment 3.

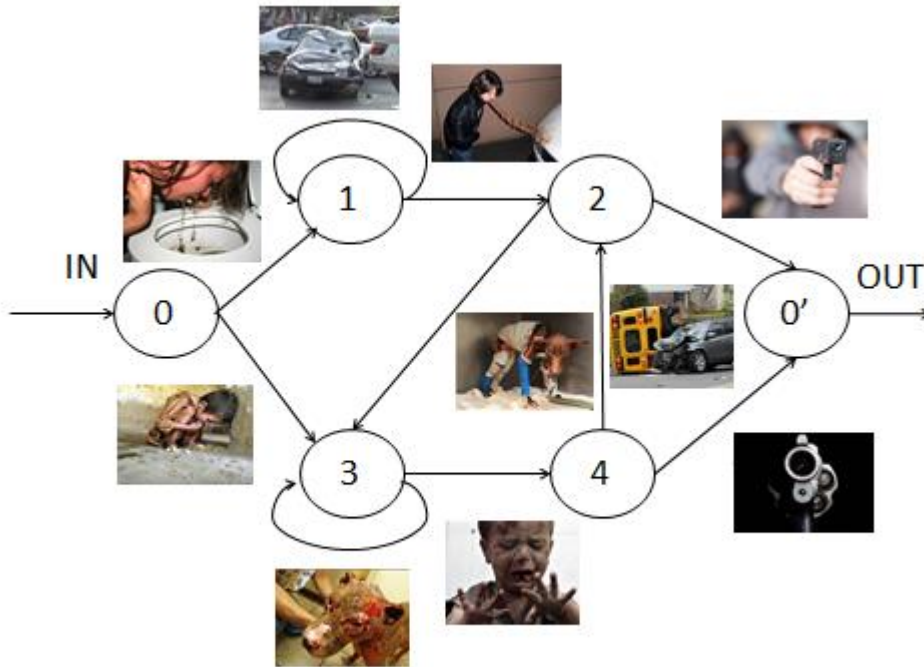


Figure 17. State diagram example for the neutral condition in Experiment 3.

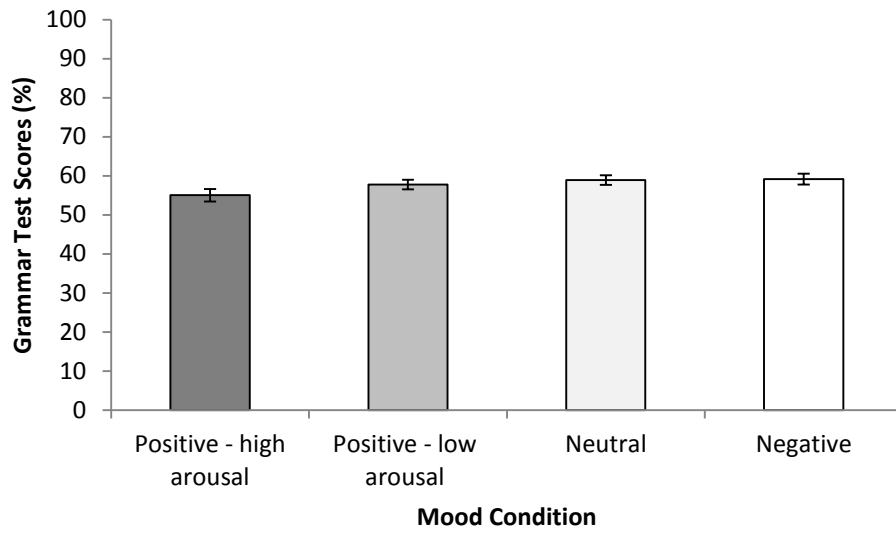


Figure 18. Mean accuracy scores for the different mood groups on the grammar test in Experiment 3. The error bars reflect standard error.

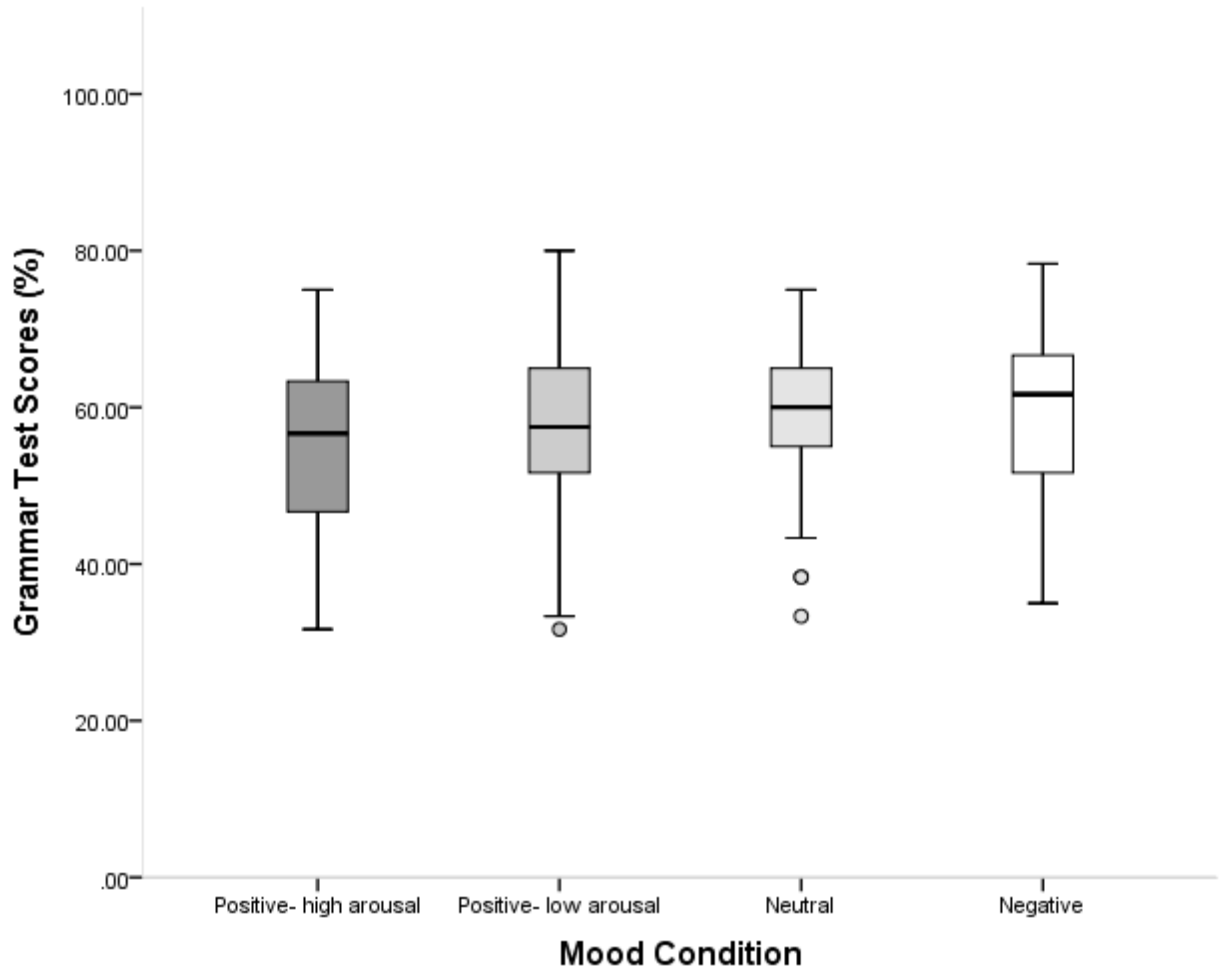


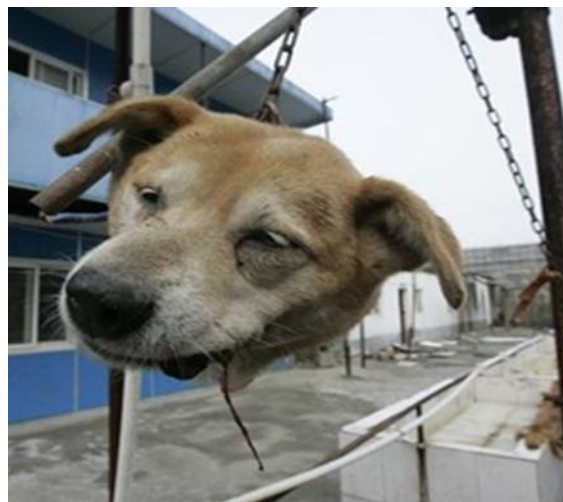
Figure 19. Boxplots for the accuracy data in Experiment 3.

APPENDIX B: PILOT IMAGES

Positive Images



Negative Images



APPENDIX C: PANAS

Positive Affect Negative Affect Schedule (PANAS)

The following 20 items describe the different types of feelings that may be experienced by a person. For each item, use the 5 point scale to rate how you are **CURRENTLY** feeling.

Interested

1	2	3	4	5
Very slightly or not at all	a little	moderately	quite a bit	extremely

Excited

1	2	3	4	5
Very slightly or not at all	a little	moderately	quite a bit	extremely

Strong

1	2	3	4	5
Very slightly or not at all	a little	moderately	quite a bit	extremely

Enthusiastic

1	2	3	4	5
Very slightly or not at all	a little	moderately	quite a bit	extremely

Proud

1	2	3	4	5
Very slightly or not at all	a little	moderately	quite a bit	extremely

Alert

1	2	3	4	5
Very slightly or not at all	a little	moderately	quite a bit	extremely

Inspired

1	2	3	4	5
Very slightly or not at all	a little	moderately	quite a bit	extremely

Determined

1	2	3	4	5
Very slightly or not at all	a little	moderately	quite a bit	extremely

Attentive

1	2	3	4	5
---	---	---	---	---

Very slightly or not at all a little moderately quite a bit extremely

Active

1
Very slightly or not at all 2 a little 3 moderately 4 quite a bit 5 extremely

Upset

1
Very slightly or not at all 2 a little 3 moderately 4 quite a bit 5 extremely

Guilty

1
Very slightly or not at all 2 a little 3 moderately 4 quite a bit 5 extremely

Scared

1
Very slightly or not at all 2 a little 3 moderately 4 quite a bit 5 extremely

Hostile

1
Very slightly or not at all 2 a little 3 moderately 4 quite a bit 5 extremely

Irritable

1
Very slightly or not at all 2 a little 3 moderately 4 quite a bit 5 extremely

Ashamed

1
Very slightly or not at all 2 a little 3 moderately 4 quite a bit 5 extremely

Nervous

1
Very slightly or not at all 2 a little 3 moderately 4 quite a bit 5 extremely

Jittery

1
Very slightly or not at all 2 a little 3 moderately 4 quite a bit 5 extremely

Afraid

1
Very slightly or not at all 2 a little 3 moderately 4 quite a bit 5 extremely

Distressed

1
Very slightly or not at all 2 a little 3 moderately 4 quite a bit 5 extremely

APPENDIX D: PILOT GRAMMAR

Simple Condition

The letter sequences that were matched to mood inducing images in the simple condition of the pilot, as well as Experiments 2- 3. The algorithm was derived for the Reber (1967) grammar. The correct sequences were presented during the training phase. The correct, consistent, and foils were used during test.

Correct

VXVS
TPTS
VXVPS
TTXVS
VVPXVS
VXXXVPS
VXVPXVS
TPPPPPTS
VVPXXVPS
TTXVPXVS
VXXXXVPS
TTXXXVPS
VVPS
TPPPTS
VVPXXVS
TPTXXVPS
TPTXXXVS
VXXXXVS
TPPTXXVS
VXXXXXVS

Consistent

VXXVS
TPPTS
TTXXVS
VXXXVS
TTXVPS
VXXVPS
TPTXVS
VVPXVPS
TPPTXVS
TTXXVPS
TTXXXVS
TPTXXVS
TPTXVPS
TPPPPTS
VXXVPXVS
TTXXXXVS
TPPPTXVS
TPPTXVPS
VXVPXXVS
VXVPXVPS

Foils

VTPS
TVXS
TXPPS
VTPXS
VTTTPS
TVXPPS
VTTPXS
TXPPXS
TXPTTPS
VPXPTPS
TVVXPPS
TXPTPX
VPXPPXS
TVVXPPXS
VTTTTTPXS
VPXPTPX
VTPXPTPS
VPXPTTPS
TVVXPPS
TXPTTPXS

Complex Condition

Material set for the complex condition in the pilot experiment. The letter sequences below were matched with the corresponding pictures in Figure 5 and Figure 6. The correct sequences were presented during the training phase. The correct, consistent, and foils were used during test.

Correct

MTVS
VXVS
MTVTS
MVRXS
VXRXVS
MTTTVS
VXTVRXS
VXTTVTS
MTTTTVTS
VXRXTTVS
VXTVRXMS
MVRXVRXS
VXRXTTTVS
VXVRXTVTS
VXTVRXRXS
VXRXVRXVS
MTTVRXRXS
MTTTTTTVS
VXRXRXRXS
VXVRXTTVS

Consistent

MVTS
VXTVS
VXTVTS
MVRXMS
VXRXMS
VXVRXS
MTVRXS
MVRXVTS
VXTTVS
MVRXRXS
VXRXRXVS
MTTTTTTVS
VXTVRXVS
MVRXRXMS
VXRXVRXS
MTTTTTTVTS
VXRXVRXMS
MVRXRXRXS
VXRXTTVTS
MTTTTVRXS

Foils

MRVS
VRTS
VTRS
MXRVS
MRXRTS
MXXXRVS
MRXTXRS
MRXTRVS
MXXRXRS
VTXXRVS
VTRXRTS
VTXXRVS
VRMRMRS
MXXXXRVS
MXRXTXRVS
MRXTXRXS
MRXTRXRTS
VTXXRXTRS
VRMRMTRVS
VRMRMTXRS

APPENDIX E: EXPERIMENT 1 GRAMMAR

The letter sequences used in Experiment 1, which were generated by the Reber (1967) state diagram. Participants were asked to memorize the correct-presented sequences. The correct-test, consistent, and foils were used at test.

<u>Correct- Presented</u>	<u>Test - Correct</u>	<u>Test- Consistent</u>	<u>Test - Foils</u>
VXVS	VXVS	VXXVS	VTPS
TPTS	TTXVS	TPPTS	VPXS
VXVPS	VXVPXVS	TTXXVS	TVXS
TTXVS	TTXVPXVS	VXXXVS	TVVXS
VVPXVS	VXXXXVPS	TTXVPS	VTTTPS
VXXXVPS	TPPPTS	VXXVPS	TVVVXS
VXVPXVS	VXXXXVS	TPTXVS	TVXPPS
TPPPPPTS		VVPXVPS	VPXPPS
VVPXXVPS		TPPTXVS	TVXPPXS
TTXVPXVS		TTXXVPS	VPXPTPS
VXXXXVPS		TTXXXVS	TVVXPPS
TTXXXVPS		TPTXXVS	TVXPTPS
VVPS		TPTXVPS	TXPTPXS
TPPPTS		TPPPPTS	VPXPPXS
VVPXXVS		VXXVPXVS	VTPXPPS
TPTXXVPS		TTXXXXVS	VTTTTPS
TPTXXXVS		TPPPTXVS	TVVVVVXS
VXXXXVS		TPPTXVPS	TVVXPPXS
TPPTXXVS		VXVPXVPS	TXPTTTPS
VXXXXXVS			VTTTTTPS
			TXPPXPPS
			TVVVXPPS
			TVVXPTPS
			VTPXPPS

APPENDIX F: EXPERIMENT 1 IAPS RATINGS

IAPS numbers, valence ratings, and arousal ratings for the images used in Experiment 1.

Title	IAPS #	Valence M	Arousal M
Positive Mood Condition			
Kitten	1460	8.21 (1.21)	4.31 (2.63)
Puppies	1710	8.34 (1.12)	5.41 (2.34)
Baby	2045	7.87 (1.19)	5.47 (2.34)
Baby	2070	8.17 (1.46)	4.51 (2.74)
Boy	2391	7.11 (1.77)	4.63 (2.43)
Mother	2311	7.54 (1.37)	4.42 (2.28)
Couple	2530	7.8 (1.55)	3.99 (2.11)
Wedding	4626	7.6 (1.66)	5.78 (2.42)
Seaside	5210	8.03 (1.09)	4.6 (2.48)
Sea	5825	8.03 (1.18)	5.46 (2.72)
Mountains	5600	7.57 (1.48)	5.19 (2.70)
Mountains	5700	7.61 (1.46)	5.68 (2.33)
Garden	5202	7.25 (1.44)	3.73 (2.22)
Nature	5201	7.06 (1.71)	3.83 (2.49)
Fireworks	5910	7.8 (1.23)	5.59 (2.55)
Castle	7502	7.75 (1.40)	5.91 (2.31)
Money	8501	7.91 (1.66)	6.44 (2.29)
Money	8502	7.51 (1.72)	5.78 (2.49)
HappyTeens	8461	7.22 (1.53)	4.69 (2.20)
Kids	2387	7.12 (1.58)	3.97 (2.18)

Seal	1440	8.19 (1.53)	4.61 (2.54)
PolarBears	1441	7.97 (1.28)	3.94 (2.38)
Baby	2071	7.86 (1.32)	5.00 (2.34)
Father	2057	7.81 (1.28)	4.54 (2.41)
Family	2395	7.49 (1.69)	4.19 (2.40)
Kids	2388	7.44 (1.44)	3.77 (2.21)
Romance	4622	7.46 (1.61)	4.11 (2.30)
Couple	2550	7.77 (1.43)	4.68 (2.43)
Romance	4623	7.13 (1.80)	5.44 (2.23)
Romance	4599	7.12 (1.48)	5.69 (1.94)
Courtyard	5779	7.33 (1.42)	3.57 (2.30)
Flowers	5811	7.23 (1.60)	3.30 (2.33)
Fireworks	5480	7.53 (1.63)	5.48 (2.35)
Money	8503	7.02 (1.71)	5.22 (2.59)
Children	2345	7.41 (1.72)	5.42 (2.47)
Boys	2224	7.24 (1.58)	4.85 (2.11)
Beach	5833	8.22 (1.08)	5.71 (2.66)
Nature	5780	7.52 (1.45)	3.75 (2.54)
Mountains	5660	7.27 (1.59)	5.07 (2.62)
Mountains	5631	7.29 (1.34)	3.86 (2.64)
Bunnies	1750	8.28 (1.07)	4.1 (2.31)
Monkeys	1811	7.62 (1.59)	5.12 (2.25)
Porpoise	1920	7.9 (1.48)	4.27 (2.53)
Jaguars	1722	7.04 (2.02)	5.22 (2.49)
Rafters	8400	7.09 (1.52)	6.61 (1.86)

Skydivers	8185	7.57 (1.52)	7.27 (2.08)
Waterskier	8200	7.54 (1.37)	6.35 (1.98)
Rollercoaster	8492	7.21 (2.26)	7.31 (1.64)
Sunset	5829	7.65 (1.42)	4.68 (2.45)
Sunset	5830	8.00 (1.48)	4.92 (2.65)
Neutral Mood Condition			
Chess	2840	4.91 (1.52)	2.43 (1.82)
Woman	2400	4.21 (1.34)	4.2 (2.10)
Crochet	7513	5.45 (1.40)	3.47 (2.02)
Woman	2026	4.82 (0.95)	3.4 (1.84)
Boy	2410	4.62 (1.72)	4.13 (2.29)
Girl	2411	5.07 (0.85)	2.86 (1.84)
Golf	8312	5.37 (1.41)	3.32 (2.06)
Golfer	8311	5.88 (1.67)	3.57 (2.35)
Reading	2377	5.19 (1.31)	3.50 (1.95)
Bakers	2579	5.53 (1.35)	3.85 (2.00)
Chess	2580	5.71 (1.41)	2.79 (1.78)
Sailboat	8211	5.76 (1.89)	5.36 (2.35)
Secretary	2383	4.72 (1.36)	3.41 (1.83)
Shopping	2745.1	5.31 (1.08)	3.26 (1.96)
Farmer	2191	5.30 (1.62)	3.61 (2.14)
Airplane	7632	5.22 (1.69)	4.78 (2.36)
Couple	2396	4.91 (1.05)	3.34 (1.83)
Baskets	7041	4.99 (1.12)	2.60 (1.78)

Puzzle	7061	5.40 (1.40)	3.66 (1.92)
FireHydrant	7100	5.24 (1.20)	2.89 (1.70)
Stove	7077	5.12 (1.46)	4.61 (2.06)
Tissue	7950	4.94 (1.21)	2.28 (1.81)
AbstractArt	7185	4.97 (0.87)	2.64 (2.04)
Cabinet	7705	4.77 (1.02)	2.65 (1.88)
Chair	7235	4.96 (1.18)	2.83 (2.00)
Outlet	6150	5.08 (1.17)	3.22 (2.02)
Stool	7025	4.63 (1.17)	2.71 (2.20)
Lamp	7175	4.87 (1.00)	1.72 (1.26)
Umbrella	7150	4.72 (1.00)	2.61 (1.76)
FileCabinets	7224	4.45 (1.36)	2.81 (1.94)
Clock	7211	4.81 (1.78)	4.2 (2.40)
Plate	7233	5.09 (1.46)	2.77 (1.92)
IroningBoard	7234	4.23 (1.58)	2.96 (1.90)
Pig	1350	5.25 (1.96)	4.37 (1.76)
DogRace	1505	4.13 (1.66)	4.73 (1.83)
Bees	1390	4.50 (1.56)	5.29 (1.97)
Gannet	1450	6.37 (1.62)	2.83 (1.87)
Buffalo	1675	5.24 (1.48)	4.37 (2.15)
Jellyfish	1908	5.28 (1.53)	4.88 (2.15)
Bridge	7546	5.4 (1.13)	3.72 (2.16)
Bridge	7547	5.21 (0.96)	3.18 (2.01)
Stairs	7504	5.67 (1.46)	4.25 (2.27)

Building	7500	5.33 (1.44)	3.26 (2.18)
Store	7495	5.90 (1.60)	3.82 (2.33)
Building	7491	4.82 (1.03)	2.39 (1.90)
Shipyards	7036	4.88 (1.08)	3.32 (2.04)
Trains	7037	4.81 (1.12)	3.71 (2.08)
Satellite	5471	5.21 (1.18)	3.26 (2.05)
Traffic	7590	4.75 (1.55)	3.80 (2.13)
Freeway	7560	4.47 (1.65)	5.24 (2.03)
Negative Mood Condition			
Hospital	2205	1.95 (1.58)	4.53 (2.23)
Funeral	2799	2.42 (1.41)	5.02 (1.99)
Cemetery	9220	2.06 (1.54)	4.00 (2.09)
GrievingFem	2141	2.44 (1.64)	5.00 (2.03)
Baby	2053	2.47 (1.87)	5.25 (2.46)
BlackEye	2345.1	2.26 (1.46)	5.50 (2.43)
StarvingChild	9075	1.66 (1.10)	6.04 (2.40)
Toddler	2095	1.79 (1.18)	5.25 (2.34)
InjuredDog	9184	2.47 (1.52)	5.75 (2.43)
HurtDog	9183	1.69 (1.10)	6.58 (2.12)
InjuredDog	9187	1.81 (1.36)	6.45 (2.30)
SickKitty	9561	2.68 (1.92)	4.79 (2.29)
Garbage	9290	2.88 (1.52)	4.40 (2.11)
Garbage	9291	2.93 (1.19)	4.38 (2.05)
Garbage	9340	2.41 (1.48)	5.16 (2.35)

Garbage	9295	2.39 (1.30)	5.11 (2.05)
Soldier	9421	2.21 (1.45)	5.04 (2.15)
Soldier	9420	2.31 (1.59)	5.69 (2.28)
Bomb	9424	2.87 (1.62)	5.78 (2.12)
Assault	9427	2.89 (1.47)	5.50 (2.09)
CarAccident	9900	2.46 (1.39)	5.58 (2.13)
CarAccident	9901	2.27 (1.25)	5.70 (2.22)
CarAccident	9908	2.34 (1.49)	6.63 (2.13)
CarAccident	9910	2.06 (1.26)	6.2 (2.16)
Fire	9921	2.04 (1.47)	6.52 (1.94)
Flood	9927	2.71 (1.56)	5.29 (1.91)
Explosion	9940	1.62 (1.20)	7.15 (2.24)
PlaneCrash	9050	2.43 (1.61)	6.36 (1.97)
DrugAddict	2710	2.52 (1.69)	5.46 (2.29)
DrunkDriving	2751	2.67 (1.87)	5.18 (2.39)
Cigarette	9831	2.95 (1.72)	4.61 (2.34)
Needles	9007	2.49 (1.41)	5.03 (2.32)
CryingBoy	2900.1	2.56 (1.41)	4.61 (2.07)
Girl	2276	2.67 (1.66)	4.63 (1.93)
KidCry	2301	2.78 (1.38)	4.57 (1.96)
ScaredChild	9041	2.98 (1.58)	4.64 (2.26)
Attack	6563	1.77 (1.23)	6.85 (2.18)
AimedGun	6250	2.83 (1.79)	6.54 (2.61)
AimedGun	6200	2.71 (1.58)	6.21 (2.28)

AimedGun	6243	2.33 (1.49)	5.99 (2.23)
Abduction	6312	2.48 (1.52)	6.37 (2.30)
BeatenFem	6315	2.31 (1.69)	6.38 (2.39)
Attack	6360	2.23 (1.73)	6.33 (2.51)
Attack	6530	2.76 (1.86)	6.18 (2.02)
Hospital	3220	2.49 (1.29)	5.52 (1.86)
DyingMan	3230	2.02 (1.30)	5.41 (2.21)
BurnVictim	3215	2.51 (1.32)	5.44 (2.16)
Surgery	3213	2.96 (1.94)	6.82 (2.00)
KKKrally	9810	2.09 (1.78)	6.62 (2.26)
Skinhead	9800	2.04 (1.57)	6.05 (2.71)

APPENDIX H: EXPERIMENT 2 IAPS RATINGS

The IAPS title, number, mean valence, and mean arousal for the images used in Experiment 2.

Title	IAPS #	Valence M	Arousal M
Positive-High Arousal			
Erotic Couple	4607	7.03 (1.84)	6.34 (2.16)
Erotic Couple	4608	7.07 (1.66)	6.47 (1.96)
Erotic Couple	4660	7.40 (1.36)	6.58 (1.88)
Erotic Couple	4680	7.25 (1.83)	6.02 (2.27)
Waterfall	5260	7.34 (1.74)	5.71 (2.53)
Astronaut	5470	7.35 (1.62)	6.02 (2.26)
Fireworks	5480	7.53 (1.63)	5.48 (2.35)
Sky Divers	5621	7.57 (1.42)	6.99 (1.95)
Wind Surfers	5623	7.19 (1.44)	5.67 (2.32)
Hiker	5629	7.03 (1.55)	6.55 (2.11)
Mountains	5700	7.61 (1.46)	5.68 (2.33)
Beach	5833	8.22 (1.08)	5.71 (2.66)
Turkey	7230	7.38 (1.65)	5.52 (2.32)
Ice Cream	7270	7.53 (1.73)	5.76 (2.21)
Cupcakes	7405	7.38 (1.73)	6.28 (2.16)
Skier	8034	7.06 (1.53)	6.30 (2.16)
Parachute	8163	7.14 (1.61)	6.53 (2.21)
Cliff Divers	8180	7.12 (1.88)	6.59 (2.12)
Roller coaster	8492	7.21 (2.26)	7.31 (1.64)

Money	8501	7.91 (1.66)	6.44 (2.29)
Positive-Low Arousal			
Seal	1440	8.19 (1.53)	4.61 (2.54)
Polar Bear	1441	7.97 (1.28)	3.94 (2.38)
Kitten	1460	8.21 (1.47)	4.31 (2.63)
Bunnies	1750	8.28 (1.07)	4.10 (2.31)
Father	2057	7.81 (1.28)	4.54 (2.41)
Neut baby	2260	8.06 (1.42)	4.26 (2.44)
Mother	2311	7.54 (1.37)	4.42 (2.28)
Baby	2070	7.69 (1.59)	4.02 (2.30)
Kids	2388	7.44 (1.44)	3.77 (2.21)
Couple	2530	7.80 (1.55)	3.99 (2.11)
Couple	2550	7.77 (1.43)	4.68 (2.43)
Baby	2660	7.75 (1.48)	4.44 (2.41)
Romance	4622	7.46 (1.61)	4.11 (2.30)
Seagulls	5831	7.63 (1.15)	4.43 (2.49)
Happy Teen	8461	7.22 (1.53)	4.69 (2.20)
Seaside	5210	8.03 (1.09)	4.60 (2.48)
Sky	5594	7.39 (1.45)	4.15 (2.76)
Mountain	5814	7.15 (1.54)	4.82 (2.40)
Beach	5836	7.25 (1.39)	4.28 (2.41)
Desert	7580	7.51 (1.60)	4.59 (2.72)
Neutral			
Pig	1350	5.25(1.96)	4.37 (1.76)

Bees	1390	4.50 (1.56)	5.29 (1.97)
Jellyfish	1908	5.28 (1.53)	4.88 (2.15)
Man	2002	4.95 (1.36)	3.35 (1.87)
Neut Face	2200	4.79 (1.38)	3.18 (2.17)
Reading	2377	5.19 (1.31)	3.50 (1.95)
Girl	2411	5.10 (0.80)	2.71 (1.74)
Neutral Male	2493	4.82 (1.27)	3.34 (2.10)
Chess	2840	4.91 (1.52)	2.43 (1.82)
Teenager	2870	5.17 (0.94)	2.87 (1.75)
Satellite	5471	5.21 (1.18)	3.26 (2.05)
Mushrooms	5532	5.19 (1.69)	3.79 (2.20)
Outlet	6150	5.08 (1.17)	3.22 (2.02)
Mug	7009	4.93 (1.00)	3.01 (1.97)
Shipyard	7036	4.88 (1.08)	3.32 (2.04)
Lamp	7175	4.87 (1.00)	1.72 (1.26)
Bridge	7547	5.21 (0.96)	3.18 (2.01)
Freeway	7560	4.47 (1.65)	5.24 (2.03)
Rolling Pin	7000	5.25 (1.38)	1.36 (1.10)
Golf	8312	5.37 (1.41)	3.32 (2.06)

Negative

Drug Addict	2717	2.58 (1.32)	5.70 (2.16)
Mutilation	3150	2.26 (1.57)	6.55 (2.20)
Infant	3350	1.88 (1.67)	5.72 (2.23)
Aimed Gun	6230	2.37 (1.57)	7.35 (2.01)
Attack	6550	2.73 (2.38)	7.09 (1.98)

Attack	6560	2.16 (1.41)	6.53 (2.42)
Suicide	6570	2.19 (1.72)	6.24 (2.16)
Roach On Pizza	7380	2.46 (1.42)	5.88 (2.44)
Starving Child	9075	1.66 (1.10)	6.04 (2.40)
Hurt Dog	9183	1.69 (1.10)	6.58 (2.12)
Injured Dog	9187	1.81 (1.36)	6.45 (2.30)
Vomit	9322	2.24 (1.24)	5.73 (2.28)
Vomit	9325	1.89 (1.23)	3.22 (1.96)
Cat	9571	1.96 (1.50)	5.64 (2.50)
Man on Fire	9635.1	1.90 (1.31)	6.54 (2.27)
KKK rally	9810	2.09 (1.78)	6.62 (2.26)
Car Accident	9900	2.46 (1.39)	5.58 (2.13)
Car Accident	9902	2.33 (1.38)	6.00 (2.15)
Car Accident	9911	2.30 (1.37)	5.76 (2.10)
Fire	9921	2.04 (1.47)	6.52 (1.94)

APPENDIX I: TABLES

Table 1. Signal detection analysis for correct items on the grammar test in Experiment 1.

Condition	Hit Rate	Miss Rate	CR Rate	False Alarm	d'	c
Positive	0.598	0.402	0.615	0.385	0.559	0.025
Neutral	0.560	0.440	0.566	0.434	0.352	0.042
Negative	0.688	0.312	0.610	0.390	0.717	-0.055

Table 2. Signal detection analysis for consistent items on the grammar test in Experiment 1.

Condition	Hit Rate	Miss Rate	CR Rate	False Alarm	d'	c
Positive	0.611	0.389	0.615	0.385	0.628	-0.0072
Neutral	0.607	0.393	0.566	0.434	0.475	-0.020
Negative	0.634	0.366	0.610	0.390	0.683	-0.036

Table 3. Mean and standard deviation PANAS scores for Experiment 2 for pre and post mood induction.

Measure of mood	Mood Condition							
	Positive-HA		Positive-LA		Neutral		Negative	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post
PANAS positive	31.17 (7.94)	20.15 (8.37)	30.64 (7.81)	23.89 (10.12)	32.94 (7.87)	19.79 (8.56)	32.74 (7.71)	21.70 (8.27)
PANAS negative	15.17 (5.16)	14.85 (4.78)	15.11 (6.98)	14.00 (4.46)	16.26 (5.84)	14.02 (3.65)	14.19 (4.28)	16.11 (5.65)

Table 4. Signal detection analysis for correct items on the grammar test in Experiment 2.

Condition	Hit Rate	Miss Rate	CR Rate	False Alarm	d'	c
Positive-HA	0.661	0.340	0.618	0.382	0.752	0.033
Positive-LA	0.658	0.342	0.601	0.399	0.5210	-0.01
Neutral	0.664	0.336	0.540	0.461	0.460	-0.048
Negative	0.629	0.371	0.600	0.403	0.614	-0.006

Table 5. Signal detection analysis for the consistent items on the grammar test in Experiment 2.

Condition	Hit Rate	Miss Rate	CR Rate	False Alarm	d'	c
Positive-HA	0.611	0.389	0.618	0.382	0.661	0.062
Positive-LA	0.667	0.333	0.601	0.411	0.508	0.006
Neutral	0.620	0.380	0.540	0.461	0.352	0.006
Negative	0.602	0.399	0.600	0.403	0.527	0.028

Table 6. Mean valence and arousal ratings for the images used in Experiment 3.

Condition	Valence M	Arousal M
Positive-HA	6.708 (0.153)	6.196 (0.328)
Positive-LA	6.640 (0.455)	3.345 (0.333)
Neutral	4.585 (0.222)	2.335 (0.293)
Negative	2.131 (0.589)	6.586 (0.868)

Table 7. Mean and standard deviation PANAS scores for Experiment 3 for pre and post mood induction.

Measure of mood	Mood Condition							
	Positive-HA		Positive-LA		Neutral		Negative	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post
PANAS positive	30.84 (8.10)	24.56 (10.18)	32.46 (7.24)	22.92 (8.71)	28.20 (8.90)	18.18 (8.50)	30.60 (7.68)	19.62 (7.52)
PANAS negative	15.12 (5.23)	13.82 (4.80)	16.76 (6.33)	13.58 (4.80)	15.68 (6.13)	14.86 (4.68)	15.52 (6.18)	24.16 (9.66)

Table 8. Signal detection analysis for correct items on the grammar test in Experiment 3.

Condition	Hit Rate	Miss Rate	CR Rate	False Alarm	d'	c
Positive-HA	0.585	0.415	0.481	0.519	0.160	-0.126
Positive-LA	0.603	0.397	0.511	0.489	0.325	-0.130
Neutral	0.641	0.359	0.522	0.478	0.440	-0.130
Negative	0.654	0.346	0.453	0.547	0.265	-0.082

Table 9. Signal detection analysis for consistent items on the grammar test in Experiment 3.

Condition	Hit Rate	Miss Rate	CR Rate	False Alarm	d'	c
Positive-HA	0.585	0.415	0.481	0.519	0.152	-0.096
Positive-LA	0.619	0.381	0.511	0.489	0.362	-0.090
Neutral	0.605	0.395	0.522	0.478	0.345	-0.097
Negative	0.667	0.333	0.453	0.547	0.323	-0.099

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