The Development of Robust Intuitive Decision Making

In Simulated Real-World Environments

by

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ABSTRACT

Intuitive decision making refers to decision making based on situational pattern recognition, which happens without deliberation. It is a fast and effortless process that occurs without complete awareness. Moreover, it is believed that implicit learning is one means by which a foundation for intuitive decision making is developed. Accordingly, the present study investigated several factors that affect implicit learning and the development of intuitive decision making in a simulated real-world environment: (1) simple versus complex situational patterns; (2) the diversity of the patterns to which an individual is exposed; (3) the underlying mechanisms.

The results showed that simple patterns led to higher levels of implicit learning and intuitive decision-making accuracy than complex patterns; increased diversity enhanced implicit learning and intuitive decision-making accuracy; and an embodied mechanism, labeling, contributes to the development of intuitive decision making in a simulated real-world environment. The results suggest that simulated real-world environments can provide the basis for training intuitive decision making, that diversity is influential in the process of training intuitive decision making, and that labeling contributes to the development of intuitive decision making. These results are interpreted in the context of applied situations such as military applications involving remotely piloted aircraft.

DEDICATION

I would like to dedicate my dissertation to my family for always being a constant source of love, support and encouragement. Specifically, I want to thank my mother for always sacrificing to keep my head above water, for always encouraging me to succeed, and for helping me up when I fall down. Thank you also to my friends for being there, supporting me, and making me have a little fun. Last, but definitely not least, to my dearest husband, Jason for providing me with an environment within our relationship that allows me to grow and thrive. Your constant encouragement and care have helped me make it through.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1 Introduction

We make decisions during nearly every waking moment of our lives. Decisions can vary in complexity from the most simple, such as deciding what shirt to wear or what to have for breakfast, to the more complex, such as deciding which house or vehicle to purchase, the next play of the team you are coaching, or how to react in a tactical military situation. The previous examples of decision making in daily life are only a few of the types of circumstances in which we make decisions. Research into the processes underpinning decision making began decades ago (von Neumann & Morgenstern, 1944) and has persisted up to present day (Kahneman & Tversky, 1979; Kahneman & Klein, 2009; Milkman, Chugh & Bazerman, 2009).

The literature has suggested that there are two primary types of processes involved in decision making: analytic processes and intuitive processes (Lopes & Oden, 1991; Hogarth, 2001; 2005; Nygren & White, 2002; Evans, 2008; Kahneman & Klein, 2009). Analytic processes are engaged when consciously considering or deliberating multiple options. These processes are primarily a rule-based process. Thus they have been generally characterized as slow and effortful. The traditional approach to studying analytic decision making processes, which is typically conducted in a laboratory setting with context-free environments, has shown that, in general, we do not make subjective, probabilistic decisions under uncertainty very well (e.g. Kahneman & Tversky, 1979; Milkman et al., 2009).

In contrast, intuitive decision making processes are relatively automatic, procedural, and therefore entail less awareness on the part of the decision maker

(Evans, 2008). Thus, these processes are generally characterized as being relatively fast, given that they involve context-dependent situational pattern recognition; and also operate well under conditions of high uncertainty and time pressure (Klein, 1989; 1998; 2008). A more recent approach to studying intuitive decision making, which primarily involves field studies of expert decision makers acting in real-world situations, is called naturalistic decision making (Klein, 1989; 1998; 2008) and is an approach that eschews the context-free paradigms of the traditional approach discussed above.

Naturalistic decision making is considered here and by others (Klein, 1989; 1998; 2008) to be driven by the concept of the recognition primed decision model (Klein, 2008). The recognition primed decision model (RPD model), describes how people use their experiences within a given domain to learn how to combine experiences into patterns and recognize situational patterns within that domain. Furthermore, the RPD model proposes that there are two processes at work when making decisions in naturalistic environments. The core of the RPD model is the intuitive aspect that is in control of the situational pattern recognition and matching process, whereas the analytic aspect is used for mental simulation and comparison of possible alternative situations and patterns.

Given its general characteristics, the intuitive decision making process associated with decision making in naturalistic settings should be particularly useful in tactical, time-compressed situations. That is, the situational pattern recognition process should allow individuals to make fast decisions without invoking full awareness and conscious deliberation. The naturalistic decision making philosophy does not propose that the intuitive process is the only process involved when making decisions in real-world situations as discussed above (see Klein, 1989; 1998; 2008; and Kahneman & Klein, 2009). However, there is also not a considerable body of research involving systematic investigations into the mechanisms underlying intuitive decision making processes. Therefore, the purpose of the present study was to investigate properties of the pattern recognition process that underlies intuitive decision making.

Non-analytical category formation

It is generally accepted that the situational pattern recognition process, and thus the intuitive decision making process, are dependent upon a form of non-analytical category formation (Brooks, 1978; Brooks & Vokey, 1991; Raab & Johnson, 2008). Such categories serve in the role of cognitive templates to which current situations are matched. The non-analytical categories are formed, or learned, through exposure to past experiences, which are called exemplars (e.g. Posner & Keele, 1968; Rehder & Hastie, 2004). An exemplar is an experience or event that induces the development of a template or schema that is stored or represented in memory. Specifically, as an individual is exposed to exemplars, he or she is thought to use inductive reasoning to infer properties about conceptual categories based on a combination of family resemblance, functional coherence and conditional probabilities (Rosch, 1978; Rehder & Hastie, 2004).

When an individual encounters a novel situation, attributes about this new experience are classified as being a member of a given category (Klein, 1998; Heit, 2000; Holyoak, Gentner, Kokinov, 2001; Rehder & Hastie, 2004). To enable this categorization process, analogy is used to transfer inferences across domains based on similarity of their relations among elements. As discussed by Hofstadter (2001) and Brooks (1978), analogy is generally non-analytical, relatively automatic, and efficient. Due to these properties, analogy likely plays a role in intuitive decision making. The categorization process depends upon memory representations, the nature of which has been the subject of continued controversy for many decades (Posner & Keele, 1968, Homa, 1984, Nosofsky & Zaki, 1998).

In this controversy generally, two types of memory representations have been proposed: exemplar and prototype (Homa, 1984; Shin & Nosofsky, 1992; Nosofsky & Zaki, 1998). Exemplars, as mentioned previously, are considered to be a form of memory representation derived from individual experiences. Exemplar models propose that the subsequent recognition and categorization of an exemplar is determined by the degree of similarity among current and previous exemplars (Homa, 1984; Shin & Nosofsky, 1992; Nosofsky & Zaki, 1998). Research has demonstrated that this degree of similarity is based on an absolute summed similarity metric, which is anchored to the individual exemplars (Nosofsky & Zaki, 1998). Evidence in support of exemplar models has been derived from studies that have shown that the specific exemplars can be recognized even when the total number of exemplars is increased (for further discussion see Homa, 1984; Nosofsky & Zaki, 1998).

In contrast, prototypes are considered to be a different form of memory representation that is derived from an abstracted or integrated average of the exemplars to which one is exposed (i.e. an ideal representation; Posner & Keele, 1968; Homa, 1984; Homa, Proulx, & Blair, 2008). Prototype frameworks propose that prototypes, abstractions or integrations of the most common elements that occur together within the exemplars, are used to define the extent of the category (Homa & Vosburgh, 1976). Interestingly, the prototype of a category is not considered to be fixed but can be altered by exposure to additional exemplars (e.g. Posner & Keele, 1968; Homa & Vosburgh, 1976). Evidence in support of prototype frameworks have been derived from studies that have revealed that prototypes of a category can be recognized even though the prototype has never been encountered previously (Franks & Bransford, 1971; Homa & Vosburgh, 1976; Homa, 1984; Minda & Smith, 2001).

The debate as to whether the categorization process consists of exemplar or prototypes has been enduring, and yet overly simplified. This oversimplification arises from the assumption that an abstraction process is involved in forming prototypes but not in representing exemplars (Nosofsky & Zaki, 1998). However, it seems reasonable to conjecture that detecting similarity among exemplars in order to categorize them should require at least some elementary form of abstraction. As a result, the notion that the process of categorization occurs only for prototypes is overly simplistic. Recently, some authors (see Malt, 1989; Smith & Minda, 1998; Minda & Smith 2001, Homa, Proulx & Blair, 2008) have argued for a framework in which exemplars and prototypes both are outcomes derived within a single categorization process.

In particular, the proposed mixed categorization process would likely be affected by the complexity of the categories. That is, the categories themselves would force the representation and use of exemplars, prototypes, or both. For example, it has been demonstrated that the level of complexity of the categories may alter their learning, such that smaller categories (less differentiated, less complex) tend to favor the learning of exemplars, whereas larger categories (more differentiated, more complex) tend to promote the learning of prototypes (Smith & Minda, 1998; Minda & Smith, 2001), although in some situations both exemplars and prototypes may be learned together (e.g. Homa, Proulx & Blair, 2008). Smith and Minda (1998) examined category learning over time for both smaller and larger categories. They found that when learning to discriminate between different category sizes and complexities, over a period of time, individuals will transition from exemplar to prototype coding, and that this transition is dependent on the time requirements inherent to the discrimination. Thus, the size and complexity of the categories will determine whether a representation involves either exemplars, prototypes, or both.

Turning back to non-analytical category formation, it is interesting to note that this process of development of a representation of non-analytical categories, through exposure to exemplars, is believed to involve an implicit learning process (Lopes & Oden, 1991). Implicit learning refers to learning that typically occurs without explicit intention, without full awareness of what has been learned, and possibly without the presence of feedback or knowledge of results to guide learning (e.g., Reber, 1989; Aslin, Saffran & Newport, 1998; Perruchet & Pacton, 2006). Many different paradigms have been used to examine implicit learning processes, a few examples of which include: perceptual and motor learning

(Gibson & Gibson, 1955; Turvey, 1990), artificial grammar learning (e.g. Reber, 1967, 1969, 1989; Mathews, Buss, Stanley, Blanchard-Fields, Cho & Druhan, 1989), statistical learning (Aslin, Saffran, & Newport, 1998; Fiser & Aslin, 2001;2002; Marsh & Glenberg, 2010), sequence learning (Gomez, Gerken, & Schvaneveldt, 2000), and the learning of the temporal order of images of objects and events (Brady & Oliva, 2008; Patterson, Pierce, Bell, Andrews & Winterbottom, 2009; Boydstun, Patterson, Pierce, Park & Shannan, 2010).

As detailed above there are many different experimental paradigms, forms of stimuli, and contexts in which implicit learning can develop. Based on these findings, it seems reasonable that others have proposed that implicit learning is generally considered to be a primitive, robust phenomenon which involves the ability to relate spatial and temporal patterns as they unfold in the environment (Fiser & Aslin, 2001, 2002; Patterson et al., 2009). Furthermore, implicit learning of non-analytical categories provides, in part, a foundation for situational pattern recognition and intuitive decision making (Klein, 1988; 1998; 2008; Patterson et al., 2009). Implicit learning is likely the process by which tacit knowledge and procedural memory are developed and likely leads to situational pattern recognition, one of the possible mechanisms underlying intuitive decision making (Reber, 1989; Patterson et al., 2009).

Intuition, and more specifically intuitive decision making, are broad concepts which date back to Plato and Aristotle and have endured as topics of great interest for the history of philosophy (Wescott, 1968). Intuition is conceptualized in varying ways by different individuals. Generally, intuition is conceptualized as a kind of knowledge that cannot be fully explained by explicit knowledge. Intuitive decision making (see Klein, 1988; 1998; 2008; Patterson et. al, 2009) refers to a form of decision making that is largely implicit and cannot be explained entirely by explicit, deliberative processes. In this context, intuitive decision making can be conceptually connected to implicit learning, tacit knowledge, and procedural knowledge.

With respect to training intuitive decision making, several authors (Reber, 1989, 1993; Hogarth, 2001; Evans, 2008; Patterson et al., 2009) contend that implicit learning is one of the ways by which intuitive decision making ability is acquired. Additionally, it has been found that there could be explicit training procedures (like memorization) that can also increase the ability of an individual to make decisions based on implicit learning (i.e. Reber, 1989, 1993). In these studies by Reber, participants were memorizing the sequences of letters and he found generally that they were still using implicit processes to abstract the underlying patterns. They were able to perform the discriminations at test, though they demonstrated overall lower performance than participants who learned in the passive learning condition. Thus, learning can be of a form which follows explicit training such as memorization, but which still leads to the underlying implicit abstraction process. However, in this investigation, the passive learning process was explored within the context of implicit learning. The passive learning explored here was of a form that would occur within a naturalistic environment where via locomotion and interaction with the environment, individuals abstract environmental relationships without awareness and without intention.

Although tasks which require participants to explicitly learn are more in line with traditional approaches to cognition, they are still in the realm of the analytic. Thus, in order to develop the ideas and conceptualization of decision making, which relies on both an analytical and intuitive processes (Klein, 1988; 1998; 2008), it is necessary to investigate how the intuitive component is learned via experience in the world. Furthermore, even though explicit learning may also lead to implicit learning, perceptual learning performed within naturalistic settings typically occurs in a somewhat passive manner in which the person is not directly trying to learn. Consistent with the approaches taken by Reber et al. (1989), Reber (1993), Hogarth (2001), Evans (2008) and Patterson et al. (2009), I will assume that implicit learning is one of the primary vehicles by which intuitive decision making is developed.

Complexity and non-analytical categories

When making intuitive decisions in real-world situations, the process of forming and utilizing non-analytical categories may be affected by the complexity of the situation. Situational complexity is generally a multifaceted issue. Here, situational complexity is discussed as it pertains to the following: (1) environmental complexity; (2) category complexity; and (3) task complexity.

The first factor contributing to situational complexity is environmental complexity. Environmental complexity is produced by the diversity and interaction of cues and patterns in the environment. These cues and their associated patterns can be multivariate, higher-order and/or multimodal. Furthermore, complex environments can lead to more cognitively demanding situations, given that an individual will need to integrate and encode the set of cues and their interactions in memory. These cognitively demanding situations may exceed the temporal and processing capacity of working memory (Cowan, 2000) generally associated with analytical processes. Intuitive processes, on the other hand, are more reliant on procedural memory and are not thought to draw on capacity-limited working memory (Evans, 2008). Thus, when environmental complexity is high, it has been found that intuitive decision making is likely a more efficient option, given that intuitive decision making is suited for situations involving high uncertainty, time pressure, changing goals, and high stakes (e.g. Klein, 1989; 1998; 2008; Zsambok & Klein, 1997). On the other hand, when interacting and making analytical decisions within a complex situation, as described above, the ability to make such decisions would likely be degraded.

The second factor contributing to situational complexity is category complexity. Recall that, the complexity of the categories can impact both category formation as well as the usage of existing category representations. As discussed previously, it has been found that complexity of the categories may alter learning, such that more complex and larger categories promote the learning of prototypes (Smith & Minda, 1998; Minda & Smith, 2001). Further, some situations may also necessitate the storage and use of individual exemplars (e.g. Homa, Proulx & Blair, 2008). When using these representations, it seems reasonable to conjecture that just as environmental complexity necessitates intuitive decision making, category complexity may also call for the use of intuitive decision making to manage complex situations (as described above). Specifically, it is likely that larger, more complex categories will occur within the same complex situations involved with high levels of environmental complexity. Furthermore, it is likely that analytical decision making would be degraded in these time critical, complex situations which likely involve category complexity. Thus, category complexity will also likely necessitate the use of intuitive decision making.

The third factor contributing to situational complexity is task complexity. Task complexity is defined here as involving multiple components, and involving higher-order relations among task components. When task complexity is high, intuitive decision making may be stronger, and less reliant on working memory (as discussed above). One example of learning of the interactions between multiple higher-order dependencies which is especially relevant to this discussion is the implicit learning paradigm employed by Reber (1967, 1969). Reber's implicit learning paradigm requires that participants learn at least two symbols prior to the next symbol to learn the artificial grammar. Learning of these higher-order dependencies is only one example of task complexity. Many other examples of task complexity exist such as dual or even multi-tasks, tasks which require split attention, and tasks involving dynamic situations. These types of tasks will introduce even more complexity into category formation, representation and utilization.

In summary, non-analytical category formation and utilization can be affected by situational complexity which, in turn, can be conceptualized to involve three components, namely the complexity of the environment, of the categories themselves, or of task performance. Two of these components are important for distinction here, as they will directly shape the discussion that follows. In particular, the complexity of the categories can influence exemplar and prototype utilization which can, in turn, impact category learning and formation of associated memory representations (Posner & Keele, 1968; Malt, 1989). Furthermore, the process of using non-analytical category representations may be additionally complicated by environmental complexity. Specifically, it is the environment which can create time pressure, which in turn can create decisional uncertainty. These types of conditions which lead to significant decisional uncertainty fall within the conceptual framework of robust decision making.

Another issue that has not been addressed is the extent to which these situational patterns (here proposed to be learned via a non-analytical, implicit process) are of an abstract, symbol-based representation in accordance with more analytically-based symbolic processes. The traditional cognitive approach to representation proposes that representations consist of abstract symbols which are not directly tied to our interactions within the world (Barsalou, 1999, 2008; Glenberg, 2010; Shapiro, 2010). An alternative to this analytically based, abstract, symbol-driven process would be a process in which representations are more strongly grounded in their associated experiences and thus would contain more ecologically driven representations of the information which are directly linked to experience.

As proposed here, the intuitive decision making process is conceived as being non-analytical, and that the mechanism behind its development is likely implicit. Thus, it seems reasonable to conjecture that the situational patterns on which intuitive decision making is based would be directly coupled with the perception and action that an individual carries out in the world. Furthermore, that experience within the world could be learned via extraction of and representation of specific components of that experience. Generally, the form of the components may be in the form of perceptual statistics such as invariants and regularities which form some fundamental opportunity for action or which have an associated meaning for an action (Gibson, 1977). Those components of experience are likely also stored or represented in some form of associated memory representation. The form of representation and their associated neural substrates remains a topic of great interest.

As discussed previously, categorization likely involves an abstraction process regardless of the associated memory representation that is formed. Here, the likely contents of abstraction in a naturalistic setting are conceived of as resembling a form of an invariant relationship present within the situational pattern within a given environment and the interactions within that environment. The associated memory representations created from this process would likely be directly grounded in the experience within the world. This suggestion is within the bounds of Barsalou’s perceptual symbol system hypothesis (1999, 2008). Barsalou proposes a theory of grounded perceptual symbols and contends that the perceptual symbols would be highly tied to both our experiences and our interactions within our environment. It is of profound interest to the current research that Barsalou’s proposal couples and grounds experience within an environment and the information contained within an associated representation. As intuitive decision making and situational pattern recognition are highly perceptual processes, then the representation of information from the world would likely be in a form of grounded symbol that was extracted via interaction with the world.

The concept of grounded symbols (Barsalou, 1999; 2008) and the proposal that associated memory representations would be linked with our experience in the world is in correspondence with an embodied approach to cognition. Generally, embodied cognition proposes that we have a much greater reliance on our bodily interactions than is generally conceived by much of cognitive psychology (Wilson, 2002; Glenberg, 2010; Shapiro, 2010). More specifically, it is proposed that a majority, if not all, of our learning from experience is driven by the way that we directly interact with the world. At the core of embodiment is the concept of Gibson's (1977) affordances; the things that we perceive and learn are the things that directly afford some form of action or interaction.

It seems likely that our experience within the world results in memory representations that are inherently grounded to that experience within the world. Thus, it also seems reasonable to conjecture that intuitive decision making would be driven by a more embodied process than would be proposed by traditional approaches to cognition. Furthermore, the type of learning that may be occurring in this paradigm may be of a form that is more tightly linked to remembering things that we encounter within the environment and which may provide opportunities for action. Specifically, it could also be conjectured that when we are navigating through our environment and learning some of the relationships between objects and actors within that environment that we construct or generate some form of label for the objects and actors and associated interactions between ourselves and those objects and actors.

Marsh and Glenberg (2010) recently investigated the forms of the labels linked to a form of grounded representation. Marsh and Glenberg suggest that there are likely three primary components to the learning process in which we can develop procedural knowledge through implicit/statistical learning. The first component of learning as proposed by Marsh and Glenberg is that people attend to stimuli and as a result of attention; they imitate the stimuli concurrently without awareness of having done so. This result is generally supported by many different examples from both behavioral and neuropsychological standpoints (Wilson, 2002).

The second component of Marsh and Glenberg's theory is that overall, imitation is considered to be a neuromuscular process. Specifically, that imitation requires neurological mechanisms tied to specific effectors (hands, feet, speech articulators). Furthermore, that these neurological mechanisms generate similar motor commands to the motor commands that would produce stimuli if there was an opportunity to act on the stimuli in a naturalistic setting (e.g. there is a neuromuscular response of the laryngeal effectors when listening to a melody, as there would be if the person were actually humming along). The neuromuscular system in implicit learning is hence proposed by Marsh and Glenberg to be "tuning" to the transitions between the states of the imitated neuromuscular systems. The intent to which the authors use tuning is in the classical perceptual sense as tuning to the given energy within the transitions. This is one manner in which Marsh and Glenberg propose that statistical properties of the sequences are learned by participants tuning their neuromuscular imitations to transitions between components within a sequence developed by a finite state algorithm.

The third component of Marsh and Glenberg's theory is that the discriminations during the test phase are based on a form of fluency of imitation. Given that the structured sequences and transitions between components of the sequences have been previously experienced during the training phase, the fluency with which they are imitated during the test phase is higher than that for non-critical sequences. Thus, because participants have previously experienced and imitated the specific transitions of the patterns, experiencing these transitions in a structured sequence would activate the same trace of the original experience and thus this would consist of a more fluent pattern. Conversely, when a person is exposed to an unstructured transition, there is no tuning of the neuromuscular system to anticipate such a transition. This lack of fluency leads to a general sense of unfamiliarity with the un-structured stimuli.

Marsh and Glenberg evaluated their proposed theory in two experiments. They used a paradigm similar to the one being used in the current investigation. The artificial grammar was used to generate structured bimodal sequences consisting of auditory tones paired with spatially defined visual stimuli. In the learning phase, participants were exposed to two sequences at a time in the bimodal grammar and were asked whether or not those two sequences were identical (all sequences were structured). In the test phase, participants were exposed to structured and unstructured sequences separated by modality (auditory only, visual only, and alternating auditory and visual). Participants were informed that all of the sequences from the training stage of the study were constructed by a set of rules, and though the sequences would no longer contain bimodal stimuli, they may still follow these rules of construction. Participants were then asked to decide if each novel sequence was generated by the same rules or different rules from the ones given at training. Marsh and Glenberg found a significant difference between performance on the separated auditory and visual discriminations and performance on the alternating sequences. This finding is accordance with both the premise that the sequences are imitated by the two different modalities and that the participants may have been learning statistics associated with transitions between the components (auditory tones and visual elements) of the sequences.

In their second experiment, Marsh and Glenberg attempted to disrupt participants' fluency in imitating the tones at test with the sequences by having the participants perform secondary tasks during test. Specifically, in the test phase, participants either 1) hummed a siren sound to interfere with the laryngeal system 2) spoke the phrase "da-da" or 3) alternated stomping with the feet. Marsh and Glenberg found that the siren task "humming" interfered with the ability to imitate humming of the auditory aspects of the sequences. This result demonstrates the use of imitation in learning transitions within the sequences of an artificial grammar. Furthermore, by disrupting the participants' ability to recall those imitations at test, Marsh and Glenberg found a significant decrease in performance on the ability to discriminate between structured and random patterns. Generally, this finding demonstrates that tuning is likely embodied in different neuromuscular systems and is not of such a form that they need to be brought to the level of awareness or that need to be made explicit in order to learn. Though the embodied mechanisms underlying implicit learning have been investigated, it is not known what role they play in the development of the situational pattern recognition process underlying robust intuitive decision making.

Robust decision making refers to decisions that are made successfully under conditions of high uncertainty and often under time pressure. Although interesting, this literature has typically dealt with the development of statistical techniques for coping with high levels of uncertainty (e.g. Krokhmal, Murphey, Pardalos, Uryasev, & Zrazhevski, 2003; Regan, Ben-Haim, Langford, Wilson, Lundberg, Andelman, & Burgman, 2005) and has focused primarily on the development of statistical approaches, incorporating concepts such as utility and probability. These studies are somewhat limited because their statistical approaches toward robustness fall under the dimension of analytical decision making. However, rather than approach robust decision making from an analytical perspective, I am interested in addressing robust decision making from an intuitive standpoint.

Robust intuitive decision making is especially desirable within environments in which complexity and high uncertainty are the norm and traditional analytical approaches would likely result in less effective decision making. Robust decision making typically emerges as a function of the complexity within a given environment and indeed, the overall situation. The environmental complexity produced by diversity and interaction of cues and patterns in the environment would likely leave a decision maker struggling to process all of the information required to enable performance of demanding tasks. Thus, the purpose of the present studies was to investigate exactly how robust intuitive decision making develops.

The results of the present study could inform the development of training regimes in a variety of different applications. Specifically relevant are tasks requiring the ability to process perceptual information in a temporally dynamic setting with situational patterns unfolding over time. It is likely that a real-world situational pattern would consist of specific combinations of cues leading up to a decision point in critical situations, and those combinations of cues would have statistical dependencies, along the same lines of the statistical dependencies examined in the current investigation. Specifically, this investigation examined how the diversity and interaction of cues and patterns affects implicit learning and therefore the development of robust intuitive decision making.

The development of robust intuitive decision making could likely be aided using simulations of real-world environments. Simulation enables realistic depictions of naturalistic environments designed to match important aspects of the real world. The United States military and the Air Force specifically have been utilizing simulation for training for over 40 years (Andrews & Bell, 2000).

Simulated environments have the advantage in that they stimulate the sensory and perceptual systems in a direct, albeit synthetic way, without the use of symbology or other elements that would require linguistically decoding and thus require extra processing time (Flin & Mitchell, 2009). Accordingly, immersive environments would be particularly useful for training within many tactical situations, although they could also be and are used successfully in more long-term strategic situations.

Simulated real-world environments, as used for training applications, have a few major advantages over traditional explicitly-driven learning methods such as classroom training. They provide the opportunity to develop expert-level proficiency while embedding the trainee in complex, dynamic tasks and situations. Currently, many training applications utilizing immersive environments are based primarily on explicit observations from Subject Matter Experts (SMEs). These training programs are developed with a general goal of making the details of performance of the task at hand explicitly available to the instructors. The approach to using SMEs to develop training syllabi and scenarios is common and generally useful. However, not everything that a trainee is required to learn or that an expert has already learned is capable of being explicitly stated.

A large proportion of expert knowledge may be in the form of procedural knowledge or stored in implicit memory, and thus may be difficult to explicitly incorporate into training requirements (Patterson et al., 2009). Additionally, there is evidence that experts when asked how they performed a task will give you the incorrect details, especially for very procedural, automatic tasks (Bargh & Morsella, 2008). To ensure that immersive environments are providing a full range of both explicit and implicit information for training intuitive decision making in complex situations, it is necessary to determine the implicit aspects of training. Additionally, it remains to be determined as to the best methods to provide implicit aspects of training to the trainee to develop expert level knowledge that enables and advances intuitive decision making skills.

In the current investigation, implicit learning was investigated utilizing a simulated, real-world environment. To do so, an implicit learning regime based on Reber's paradigm was implemented. Specifically, Reber's paradigm was extended and applied to a simulated, real-world environment depicting dynamic outdoor scenes viewed in perspective within a simulated world.

Reber (1967) had participants memorize strings of letters derived from an artificial grammar, created using a finite state algorithm (FSA) which generates an artificial language based on a specific set of rules of "sentence" construction. The paradigm has two major phases, the training and test phases. In the training phase, to the participants, the letter strings appeared as simple random strings even though the entire set of strings possessed an underlying statistical structure. In the test phase, participants were asked to transfer their learning to recognition of a novel series of strings, some of which were created using the same grammar, and some which were random. Participants were able to reliably recognize the structured sequences during the test phase demonstrating that the implicit learning that occurred in the learning phase was successfully transferred to the novel grammatical sequences they were shown in the test phase. However, participants were not able to verbalize much about how they performed the recognition, thus demonstrating that their learning was largely implicit.

The findings discussed above from Reber's original paradigm (1967) have been extended recently to include learning of sequences of objects presented within a virtual world (Patterson et al., 2009). Patterson et al. (2009) employed the same general form of implicit learning paradigm and FSA to create sequences of objects (e.g. military vehicles), each of which appeared to be random to the participants, yet the collection of sequences possessed a subtle statistical structure. Instead of memorizing strings, (as in Reber's paradigm), participants were passively exposed to the sequences of objects by being flown over the sequences embedded on terrain within a simulated, real-world environment.

Consistent with Reber's paradigm, Patterson et al.'s (2009) paradigm also contained a training and test phase. In the training phase, participants were not given any specific instruction to attend to any specific aspects of the sequences. Consistent with the paradigm used by Reber (1967), in Patterson et al., participants were only exposed to grammatical sequences during this phase due to the passive nature of the learning and the absence of feedback in the training phase. Also consistent with Reber's paradigm, after training completion, participants were informed that the set of object sequences to which they were exposed was created using an underlying rule constraining the sequences of objects. In the test phase, participants were asked to simply recognize whether sequences contained the pattern to which they were exposed (structured sequences) or were random (non-structured sequences). The provocative result from Patterson et al. (2009) was that, although participants were not directed to learn anything and were learning in an unsupervised manner without any feedback, they were able to transfer the information that they had implicitly learned about the subtle statistical structure underlying the object sequences sufficiently well enough to successfully recognize the novel structured sequences compared to the truly random sequences. Furthermore, the authors found that participants could verbalize some aspects of the patterns (i.e. pairs of stimuli or single sequences), but could not completely explicitly describe the underlying pattern, that is learning was found to be largely implicit.

The present investigations employed a paradigm similar to that used by Patterson et al. (2009) wherein a simulated, real-world environment was used to present the structured sequences to participants. The simulated, real-world environment was utilized in order to depict realistic simulations of natural environments designed to match important aspects of the real world (Andrews & Bell, 2000; Flin & Mitchell, 2009). As described previously, the research conducted by Patterson et al. (2009) into the mechanisms behind intuitive decision making have successfully demonstrated that implicit learning can occur within an simulated real-world environment with real world stimuli (i.e. objects embedded within an simulated real-world environment) and in an unsupervised learning paradigm without feedback. Furthermore, recall that the intuitive decision making process performs well in situations involving time pressure and high uncertainty (e.g. Klein, 1989; 1998; 2008), as well as in situations with changing goals, high stakes and longer time frames. However, there is currently not a line of systematic research investigating how to develop robust decision making of an intuitive form.

Purpose of Investigation

The purpose of the present research was to investigate methods for the development of robust intuitive decision making utilizing a simulated real-world environment. In doing so, I investigated how the diversity of training affects learning and its robustness, as assessed by the transfer of learning to a novel set of test episodes. Specifically, this investigation examined methods to enhance the development of robust intuitive decision making by examining the effects of exemplar diversity (i.e. breadth of experience) on implicit learning and one aspect of its robustness, namely transfer. Furthermore, in an attempt to understand the nature of the development of intuitive decision making, I also investigated a possible embodied perceptual mechanism underlying development of this crucial ability.

One goal of Experiment 1 was to establish that implicit learning of artificial episodes can occur without feedback in an unsupervised learning paradigm using a simulated, real-world environment. To do so, a FSA with a simple structure (Reber, 1967), which herein will be called the simple FSA, was employed to make contact with and replicate previous research (Patterson et al., 2009). Experiment 1 also used a more complex FSA (Reber & Allen, 1978), which herein will be called the complex FSA, to generate a sufficient number of exemplars for use in Experiment 2. Thus, a second goal of Experiment 1 was to determine whether a sufficient level of implicit learning could occur with the complex FSA. Employing a 2 x 2 factorial design, two levels of training (no training, training) were combined with two levels of FSA complexity (simple, complex) to create four experimental conditions. In this experiment, the number of exemplars used for training was eighteen, and each exemplar was repeated sixteen times. The dependent variable was percent correct recognition performance of novels structured sequences versus random sequences during the test phase.

It was predicted that the paradigm should generally serve to foster implicit learning and that performance of participants within the training groups would be greater than that of the groups who did not receive training. It was also predicted that the added complexity of the FSA could require more diversity of information and repetition of information to demonstrate implicit learning than the levels of diversity that were originally used in the experiment of Patterson et al. (2009). The need for alternate levels of diversity and repetition would be indicated by a lower level of implicit learning for the more complex grammar.

Experiment 2 assessed the impact of diversity of the sequences on implicit learning. Research on the cognitive operations of category learning and development of associated memory representations has shown that diversity (or breadth) of the exemplars within a category is influential in the process of categorization and representation. Specifically, the larger diversity of the exemplars to which participants are exposed, the more likely they are to develop a prototype (e.g. a memory representation) which can thus be transferred to a different set of stimuli and persist over time (Homa & Vosburgh, 1976). It was hypothesized here that the diversity of exemplars to which participants were exposed would affect their ability to make intuitive decisions when asked to transfer learning or knowledge from the learning set of stimuli to the novel sequences used during the test phase.

In this experiment, five levels of diversity and repetition of training exemplars were explored as well as a no-training, control condition. The complex FSA from Experiment 1 was used as it creates significantly more sequences than the simple FSA (103 sequences vs. 43 sequences respectively). Diversity was defined as the total number of different exemplars (i.e. different episodes) to which a participant was exposed. In the training phase, diversity was manipulated by holding constant the total number of exposures to the exemplars (at 288 episodes), while allowing the total number of repetitions to vary. The comparison of interest for this experiment was the change in performance with the increase in diversity and decrease in repetition. It was predicted that as diversity increased and repetition decreased, performance would also increase.

The goal of Experiment 3 was to investigate a possible mechanism behind implicit learning. In the embodied cognition literature (Marsh & Glenberg, 2010; Glenberg, 2010) it has been proposed that one method of learning for procedurally-based knowledge such as implicit learning is by neuromuscular imitations of the stimuli during learning. In the context of the present experiments, it may be that participants are labeling the stimuli, that is, using neuromuscular systems of speech articulation. Labeling successive stimuli would then set the stage for neuromuscular tuning of transitions. The labels would not only consist of labels for the objects within a given sequence but also of the transitions within the sequences of objects. Thus, it was of theoretical interest to determine whether labeling and imitation is important to implicit learning within simulated, real-world environments.

Employing a 2 x 2 factorial design, two levels of labeling during training (labeling, no labeling) were combined with two levels of suppression employed during test (toe tapping, verbal articulation) to create four experimental conditions. In the non-labeling condition, the training phase was identical to the training phase described in the general method. In the labeling condition, participants were asked to verbally label each of the objects as they encountered them in the virtual environment. During the test phase, participants were asked to perform secondary suppression tasks (articulatory suppression or toe tapping) while completing the test phase. It was predicted that participants in the non-labeling group would demonstrate similar learning to participants in the simple-algorithm, with-training group in Experiment 1. It was also predicted that participants in the labeling group would demonstrate greater levels of performance overall due to the creation of an implicit representation tied to the labels as a result of repeating the names of the vehicles during the training phase. The critical prediction was that articulatory suppression during the test phase would demonstrate interference with the ability to imitate the labels and thus affect the fluency and the usage of the labels at test. This result was predicted in accordance with the results demonstrated by Marsh and Glenberg (2010).

All experiments utilized a simulated, real-world environment as a tool to induce non-analytical categories and determine the requirements for implicit learning as a mechanism leading to the development of intuitive decision making. The simulated, real-world environment consisted of realistic terrain imagery upon which three dimensional models of vehicles were placed. The vehicles were placed in predetermined spatial locations within the virtual environment. Two finite state algorithms (FSA) were used to create the sequences of stimuli; both of which have been used in previous artificial grammar learning experiments (e.g. Reber, 1967; Reber & Allen, 1978). There are traditionally two phases within an implicit learning paradigm: training and test.

In the training phase of the experiments, an exemplar consisted of the participants experiencing simulated flight over the sequences of vehicles (for ~ 5 seconds). The number of exemplars to which participants were exposed and the number of repetitions they received varied depending on the individual experiment and conditions. After the training phase, participants were informed that the sequences of objects to which they were previously exposed had an underlying statistical pattern (they were not explicitly informed as to the specific underlying pattern). They were then asked to complete a test phase in which they were exposed to a different subset of stimuli generated using the same FSA and random stimuli and were asked to decide if each had the same statistical pattern they saw before (grammatical/structured) or not (ungrammatical/unstructured).

In this investigation, I explored the effects of exemplar diversity and a possible mechanism underlying implicit learning. It was generally predicted that there is an optimal combination of diversity that will serve to create robust intuitive decision making. Robust intuitive decision making will be indicated by participants demonstrating learning within an unsupervised learning paradigm by demonstrating transfer of training from the training set of sequences to the novel set of sequences presented during test. This result would further the development of training for robust intuitive decision making in naturalistic environments. Furthermore, labeling was investigated as a possible mechanism underlying implicit learning and thus intuitive decision making.

2 General Method

Participants

Participants were recruited from Arizona State University student populations at the Polytechnic and Tempe campuses. The number of participants is detailed separately for each experiment. All participants were given standard visual screening to ensure approximately normal vision (near visual acuity is approximately normal or corrected to normal (e.g. approximately 20/20), color vision, binocular vision, and vertical and lateral phoria). Participants provided informed consent consistent with the requirements of both the Arizona State University Institutional Review Board and the Air Force Research Laboratory Institutional Review Board.

Stimuli

Participants were seated in front of a large display upon which a dynamic scene (i.e. simulated perspective view of a natural terrain, horizon and sky) was presented. On the display, a structured set of object sequences was presented. The structured set of object sequences was composed of five vehicles (e.g. humvee, Abrams tank, Bradley tank, patriot missile launcher, and truck) positioned on the terrain, following the methods of Patterson, et al. (2009). In each episode, vehicles were placed in spatial locations that varied within a random offset (± 15 meters) midline to the direction of locomotion (as shown in Figure 1). The first vehicle occurred 250 meters from the start of an episode and 150 meters thereafter. Figure 2 depicts a computer representation of the simulated real-world environment.

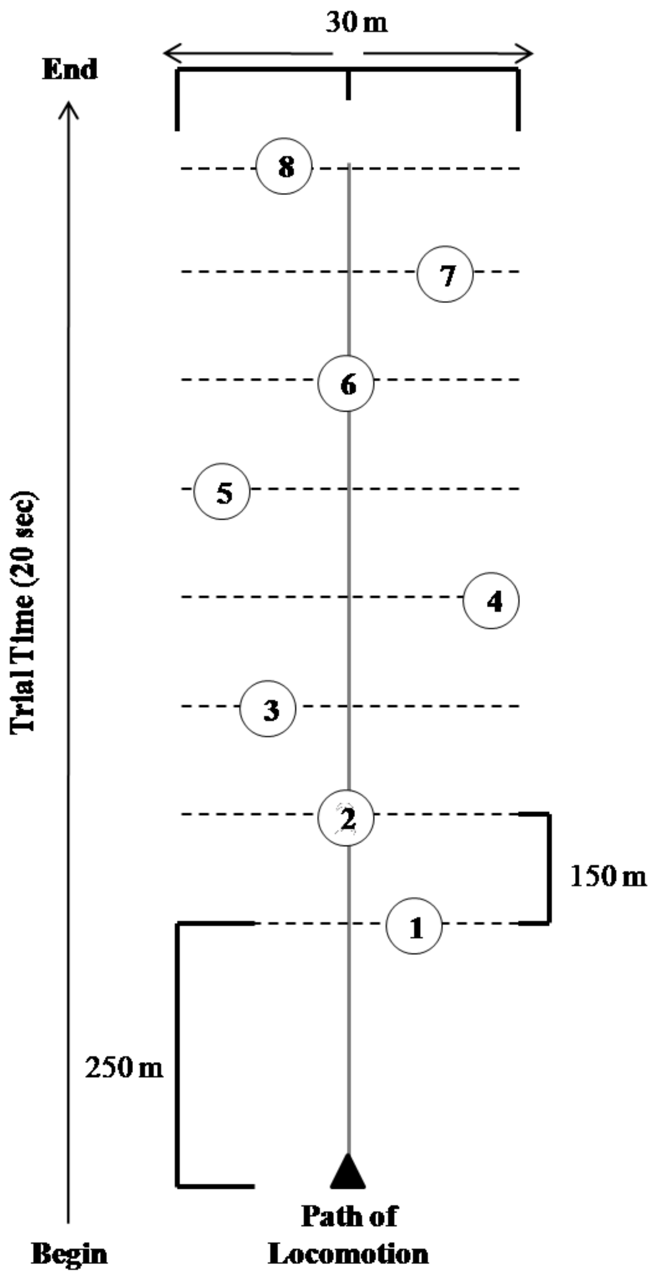


Figure 1. Depiction of starting location, distances between stimuli, and locomotion across the terrain within an episode. Object location (1-8) will vary ±15m from zero (shown in middle) for each episode/sequence of objects.

Figure 2. Image depicting the simulated real-world environment including a three-dimensional scene composed of a terrain and horizon in perspective view upon which vehicles will be positioned in a sequence stretching out along the z-axis. The scene underwent expansive optic flow motion which simulated passive movement of the participant in the forward direction toward the horizon.

The order of the vehicles was determined using a finite state algorithm (FSA) (e.g. Reber, 1967). Figure 3 depicts state diagrams of the FSAs used to construct the temporal order of the vehicles within each episode. The FSA depicted in the top portion of Figure 3 was employed in Experiments 1 and 3 (which will herein be called the simple FSA), whereas the FSA employed in the bottom portion of Figure 3 was used in Experiments 1 and 2 (which will herein be called the complex FSA). Vehicular sequences within an artificial episode began when the state diagram was entered from the left hand side and end when the last state in the diagram was exited. The algorithm selects each state randomly, but is limited by the probability of the arcs from each state as to what object can be produced. For the simple algorithm there is a 50% probability that a given state will select one of the arcs exiting the state. For the complex algorithm, the beginning states are fixed at 50% and the end states are fixed at a 33% probability of occurrence. In both diagrams, transitions from one state to another (e.g. S0 to S1) produced the temporal order of the objects in the episodes. Thus, the actual sequences and their length varied depending on the particular path followed through the algorithm. There were two loops present in each algorithm. This loop allows the pattern to repeat and acts as a salient cue for participants.

The set of all possible vehicular sequences that can be produced via a given FSA is called the 'structured set' of vehicular sequences. In the present investigation, the length of each sequence was restricted to between 4 and 8 vehicles, which produced a structured set of 42 total sequences for the simple FSA, and 103 sequences for the complex FSA. A set of quasi-random vehicular sequences, using the same set of vehicles, was also produced for use in the test phase of the experiments.

The quasi-random sequences were generated using a method to ensure that the beginning and ending objects of the sequences had the same probability of occurrence as the beginning and ending objects of the structured sequences (simple probability of occurrence at each end was 50%, complex probability of occurrence at the beginning was 50% and at the end was 33%). By fixing the ends to the same probabilities as the actual FSA sequences, the middle portions of the sequences remained truly random to the extent that the middle portions of the quasi-random sequences could be made up of any of the five objects of which the structured sequences were composed. This method ensured that sequences did not directly occur to the participants as being random.

Prior to use in the experiments, the quasi-random sequences were compared to the structured sequences to ensure that none of the random sequences were fully grammatical and did not correspond exactly to the structured sequences. However, due to the random selection of the objects for these sequences, there may have been some grammatical transitions within the sequences. There was however a violation of the algorithm contained within the random sequences therefore they are still considered to be unstructured, which is consistent with the methods used in other implicit learning experiments (Reber, 1967; Patterson et al, 2009).

Apparatus

Stimuli were displayed on a 50 inch plasma television (Panasonic Viera). Terrain imagery was generated using commercial visual simulation database development software (World Perfect 2.0, MetaVR, Inc., Brookline, MA). Flight over the terrain was simulated using a PC based runtime system (Virtual Reality Scene Generator (VRSG), MetaVR). The vehicles were created and embedded upon the terrain using a combination of World Perfect and MetaVR VRSG. A two-button controller box was used to collect responses from participants. The button box is depicted in Appendix A. Two desktop PCs were used. One of the PCs ran MetaVR VRSG and the other ran the custom software to control the timing and order aspects of the trials as well as interface with the two-button controller box. The apparatus was the same for all experiments.

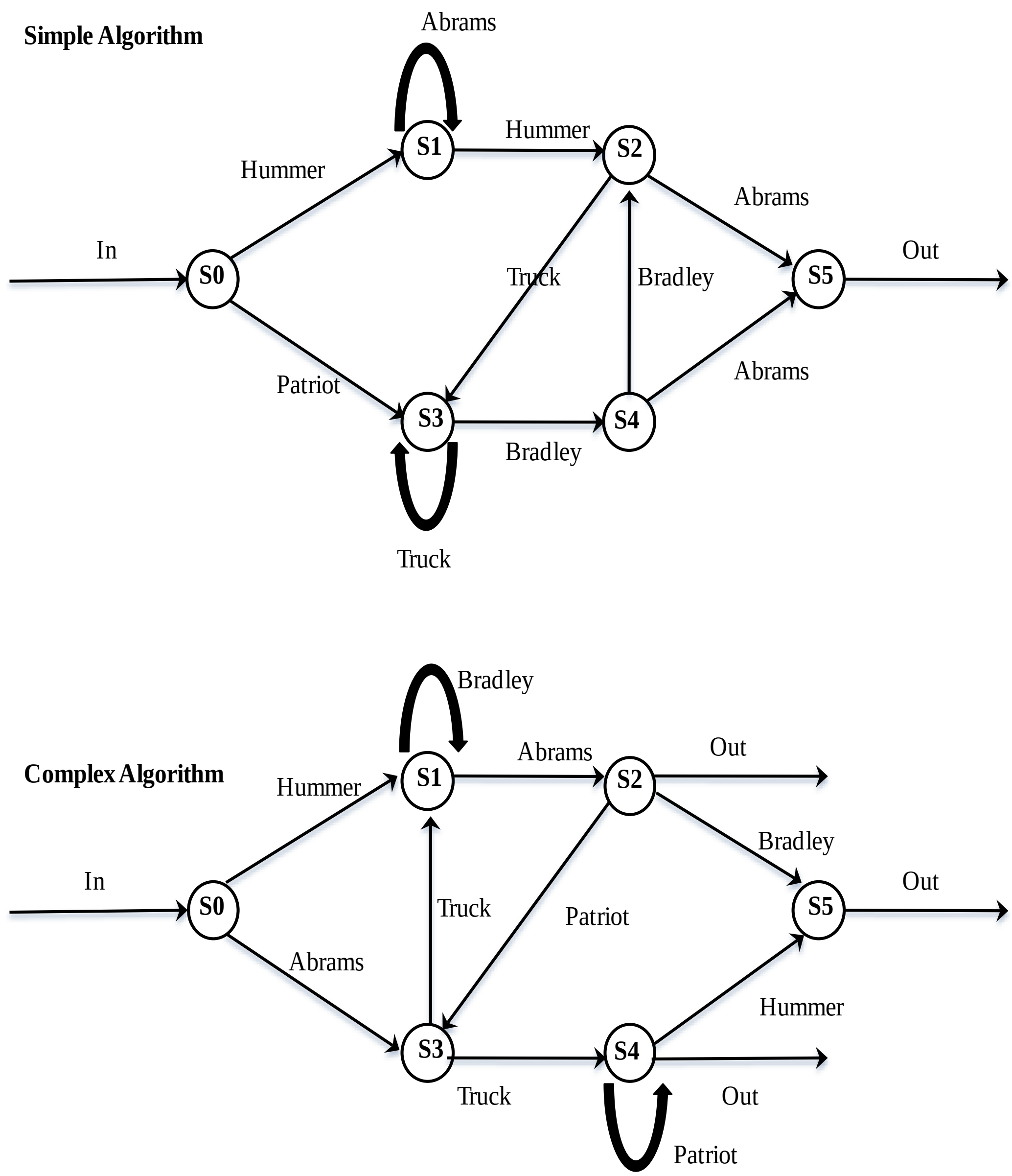


Figure 3. Top: Depiction of the Simple State Diagram after Reber (1967,1969). The algorithm has 6 states, 5 elements (vehicles), and 2 arcs (number of possible paths from each state). Also note that at states 1 and 3 there was a loop present in the grammar. This loop allows the pattern to repeat and acts as a salient cue for participants. Bottom: depiction of the Complex State Diagram after Reber & Allen (1978) consisting of 6 states, 5 elements (vehicles), and 2 to 3 arcs (number of possible paths from each state).

Procedure

In an unsupervised learning paradigm, participants were asked to simply watch a series of episodes for a period of time without any specific instruction to learn or attend without feedback. There was no measure of attention taken nor were any of the participants provided feedback or tested during learning thus in this investigation their learning was deemed “unsupervised” and their experience was deemed “passive”. An episode consisted of the participant being passively flown, for 5 seconds, over the scene toward the horizon (participants will not be required to control their altitude, speed or heading). As participants progressed through the artificial episode they encountered a scene containing a given sequence of objects (order different for each episode) one at a time.

Within an artificial episode, participants moved at a simulated speed of 250 m/sec, at an altitude of 15 m and were flown over the objects one at a time in the order specified by the FSA. Participants were seated three meters from the display and handed the button box. Customized software written in C++ and experiment specification files controlled all aspects of the experiment. Specifically, the software interacted with MetaVR to present both the learning and test phases of the experiments and controlled the duration of the episodes during training and test, the speed of locomotion through the simulated environment, and interactions with the button box to collect responses from participants.

Training Phase. Participants selected to complete the training phase were asked to observe a subset of the individual episodes. Between each episode, a blue screen (sky colored) appeared for one second, followed by the next episode. The number of novel episodes that participants received and the number of repetitions of each varied dependent on the experiment and the individual experimental condition.

Test Phase. All participants received a test phase in which they were shown presentations of novel structured sequences generated from one of the FSAs. Participants in the training groups were told that the sequences of vehicles within the set of episodes that they just watched were formed by a complex yet rigorous set of rules and thus contained an underlying structure. Specifically, the experimenter read the written instructions "The sequences of objects that you are about to see, will consist of some sequences that will follow the same rules and some which will not. It is going to be your job to determine whether you believe that the ones that you are about to see follow the same rules as the ones that you have previously viewed. Choose Y for yes or N for no on the button box." Thus, participants were asked to recognize structured episodes (generated from one of the FSAs) as compared to the non-structured episodes (random). The no-training groups were informed that some of the vehicles within the episodes had an underlying pattern and some did not. They were then also asked to recognize structured episodes in a similar manner to the training groups. Instructions for all experiments and conditions are in Appendix A. The condition labels on the instructions are for documentation purposes only.

The test procedures were similar across the experiments. All participants were exposed to twenty-two test episodes from both the structured and random sequences twice (creating a total of eighty-eight trials). Following exposure to an episode, a sky blue screen with the instruction “Push only one button” appeared on the screen and remained until participants made a selection. All participants received one episode at a time and once they responded then they received the next episode until all sequences were exhausted.

The training groups received sequences generated from the same FSA as the episodes they were exposed to in the training phase randomized with the quasi-random sequences. The no-training groups received episodes with sequences generated from one of the FSAs also randomized with the quasi-random sequences. All participants were asked to perform a two alternative forced-choice task and asked to decide whether or not a given episode in the test condition belonged to the set of episodes that they were shown in the training phase.

After the test phase was completed, each participant was asked to provide a description of the knowledge used during the test phase. One key result from the implicit learning literature is that generally, participants are unable to fully verbalize the basis of their recognition performance acquired during the training phase (Reber, 1967; Patterson et al., 2009). The lack of the ability to verbalize the basis of their performance will be considered here as evidence for implicit learning.

Data Analysis

The primary dependent variable of interest in this investigation was the percent correct of the recognition responses made by the participants in the test phase of the experiments. The responses were scored as to whether individual participants made the correct decision or not resulting in a binary index of their decision for each episode (0= incorrect; 1= correct). The responses were then averaged to create a mean rating for each trial across two instances within the recognition task. Mean recognition ratings were then averaged for each type of episode and the percent correct for each participant was calculated by dividing the total number of correct responses by the total number of episodes. The data analysis procedures are described separately for each experiment.

3 Experiment 1: Replication of Patterson et al. (2009)

The purpose of the first experiment was to make empirical contact with previous research on the implicit learning of artificial episodes presented within a simulated real-world environment. In recent research by Patterson et al. (2009), the authors investigated the implicit learning of artificial episodes within a simulated real-world environment and found that participants were able to implicitly learn the underlying statistical pattern inherent in a set of structured sequences of objects and were able to use this learning to make simple intuitive recognitions between structured and un-structured sequences. Patterson, et al. (2009) adapted the seminal implicit learning paradigm employed by Reber (1967, 1969) by using 3-D object sequences in a simulated real-world environment in lieu of letter strings.

The investigations reported here utilized a general form of the paradigm employed by Patterson et al. (2009), thus, it was deemed imperative to replicate the results from Patterson et al. The authors used the original FSA employed by Reber (1967, 1969; as depicted in Figure 3, top diagram) which provides a critical set of 41 strings. Specifically, it is of interest in this experiment to determine if the implicit learning that occurred within the paradigm used by Patterson et al. (2009) also occurs with a more complex FSA (as depicted in Figure 3, bottom diagram, as employed by Reber & Allen, 1978). Thus, this experiment endeavored to replicate the Patterson et al. paradigm and used the same FSA as well as a relatively more complex FSA (which creates 103 sequences) as the subsequent experiments required a significantly larger number of stimuli than is created by the original FSA utilized by Reber and the Patterson et al. experiments.

Two training types were explored (training vs. no training) in Experiment 1. The no training condition served to validate the test procedure. Participants in the training conditions were learning implicitly in an unsupervised learning paradigm, that is, a passive process in which they were exposed to information and without awareness, acquire knowledge of that information.

The two algorithms compared in this experiment were the simple and the complex algorithm. The simple algorithm was used in an attempt to replicate the implicit learning found in Patterson et al. (2009). The complex algorithm was used in an attempt to extend the implicit learning found in Patterson et al. (2009) to a more complex algorithm (which will be used in subsequent experiments and which was originally used by Reber & Allen, 1978). In the interest of applications to learning for military operations, military vehicles were used to create the object sequences.

Participants in both training conditions (simple vs. complex algorithm) received a predetermined set of representative structured sequences. All participants received a test phase in which they were required to recognize structured scenes. Two groups of test only participants (control groups) also received the test phase and were exposed to episodes created from one of the algorithms (simple vs. complex).

Participants who received training received a novel set of episodes during test. Because participants never were exposed to the actual episodes and sequences used during the test phase, successful performance during the test phase implies that participants transferred knowledge about the subtle underlying structure of the structured sequences during the training phase to the novel sequences used during the test phase. This transfer of implicit learning likely enabled participants to recognize the structured sequences during the test phase.

The purpose of the test-only conditions was to assess the validity of the recognition test and to ensure that participants were learning implicitly in this unsupervised learning paradigm. If participants were able to successfully recognize structured sequences at levels approximating the training conditions without any training, then the test would be deemed invalid.

Performance was measured in percent correct by assessing the participant's ability to recognize structured sequences (generated from the finite state algorithms) in comparison to the non-structured sequences (quasi-random). The purpose of the test episodes was to determine the degree to which the participants might be using non-representative rules to make their intuitive decisions, that is, decision rules that they used to make their decision, but that do not reflect the actual differences between structured and non-structured sequences (i.e., called non-representative category induction). This tendency can also be assessed by comparing the pattern of correct and erroneous classification responses participants make to each episode. An example of a non-representative rule is use of a rule stating something similar to "all pattern sequences have a repeating element" though this rule may hold for some of the structured sequences, it also holds for the unstructured sequences.

Method

Participants. Forty participants (18 males and 22 females, Mean age 23 years, Standard Deviation 5.8) were recruited from either the Polytechnic or Tempe Arizona State University campus. Participants all had approximately normal vision and provided informed consent consistent. Participants were paid 10$ for participation.

Stimuli. Details about the stimuli are provided in the general method. Only aspects which differ will be outlined here. The aspects which differ are the FSAs used, the number of sequences and the number of repetitions of each sequence.

Figure 3 depicts schematics of the simple and complex FSAs which were both used for this experiment. The top diagram in Figure 3 depicts the simple FSA originally used by Reber (1967; 1969) that has been employed in many different artificial grammar learning studies. The bottom diagram in Figure 3 depicts the complex FSA used by Reber & Allen (1978). The critical set of all possible sequences that can be generated with the two FSAs are listed in Appendix B and C. A set of alternate quasi-random vehicular sequences was also produced as described in the general method (with the same five carrier objects) for use in the test phase.

Procedure. Participants were randomly assigned to one of four groups. Out of the four groups of participants, two groups received both the training and test phases (simple vs. complex training groups), and the other two groups only received the test phases (simple vs. complex no training groups). Appendix A lists instructions for all participants.

Training Phase. Two groups of participants were selected to complete the training phase. The training phase consisted of a sample of sequences taken out of the sequence lists from the simple or complex FSA. To replicate the procedures of Patterson et al. (2009) and Reber, (1967; 1969), each participant received eighteen sequences repeated sixteen times (total of 288 trials) over a period of approximately thirty minutes. The episodes were presented in six blocks and the repetitions were presented within the blocked order. Participants were asked to passively observe the individual episodes.

Test Phase. All participants received a test phase. The two groups who completed the training phase were asked to recognize whether each individual sequence was structured (generated from one of the FSAs) or unstructured episode (quasi-random). Participants in the test only groups were informed that some of the vehicles within the episodes had an underlying pattern and some did not. They were then also asked to recognize structured from unstructured episodes. All other test procedures were as described in the general method.

Results

Responses for all participants were scored according to the approach described in the general method. To evaluate whether participants in the training conditions demonstrated implicit learning and increased performance (over chance, 50%) when compared to the no training conditions, *t*- tests were computed comparing performance within each combination of the training conditions and the algorithm complexity conditions. The results from the *t*-tests are shown in Table 1. All conditions within the experiment except for the no training, complex algorithm condition demonstrated performance significantly above chance (all $p < 0.05$).

This significant difference from chance in the no training condition was not predicted. A further analysis of participants' responses over time was completed to examine whether or not they were learning during the test. All responses for the no training participants were examined by creating means for both quarters (22 trials) and halves (44 trials) of the recognition responses in the test phase to create a metric of their decisions over time as a function of the two different complexities of algorithms. There were no significant differences within the two analyses (quarters or halves) across the two algorithms for the no training condition. Thus, given related research with a comparable design, stimuli, and procedures (i.e. Patterson et al., 2009), which showed that a no-training, control condition generally produces chance-level performance (as occurred in the no-training, complex algorithm condition), I conclude that this result is likely a type I statistical error.

Table 1. Results from t- tests for training and algorithm complexity conditions.

Training	Algorithm	*t*	*p*(2 tailed)	*M* Difference	95% CI
None	Simple	3.488	0.007*	7.386	[2.596, 12.177]
	Complex	-0.057	0.584	-1.364	[-6.794, 4.067]
Training	Simple	5.027	0.001*	19.545	[10.750, 28.341]
	Complex	3.308	0.009*	8.523	[2.695, 14.351]

Note: CI= Confidence Interval, Degrees of freedom for each test=9, $*p < 0.05$.

Figure 4 depicts group mean recognition performance in percent correct (y axis) as a function of the complexity of the algorithm (legend) and training condition (x axis). Based on the results obtained by Patterson et al. (2009) it was predicted that participants in both training groups (simple vs. complex finite state algorithm groups) would learn implicitly (performance greater than 50%) when compared to groups who did not receive training (control groups whose performance is expected to be around 50%). Even in the face of the type 1 error in the no training, simple FSA condition, participants in the training groups (M = 64.03, SD = 11.62) demonstrated higher performance than participants who did not receive the training phase (M = 53.01, SD = 8.29). A second prediction was that there would be a difference in performance due to the increase in complexity of the algorithm used to generate the sequences of objects. The performance of all participants who received the simple algorithm (used by Reber, 1967, 1969 & Patterson et al. 2009) was higher (M = 63.47, SD = 11.50) than participants who received stimuli generated by the more complex algorithm (M = 53.58, SD = 9.19).

The data shown in Figure 4 were subjected to a 2 × 2 between-subjects analysis of variance (ANOVA). This analysis shows a main effect of training condition, $F(1, 36) = 15.188$, $p < 0.001$, *partial* $\eta^2 = 0.297$, as well as a main effect of algorithm complexity, $F(1, 36) = 12.22$, $p < 0.001$, *partial* $\eta^2 = 0.253$. This analysis did not reveal an interaction between training and algorithm complexity, $F(1, 36) = 0.161$, $p = 0.69$, *partial* $\eta^2 = 0.004$. An ANOVA was also conducted to examine the effect of complexity on implicit learning in the training condition shows that there was a difference between the simple and complex FSA performance with training $F(1, 18) = 5.585$, $p < 0.05$, *partial* $\eta^2 = 0.237$.

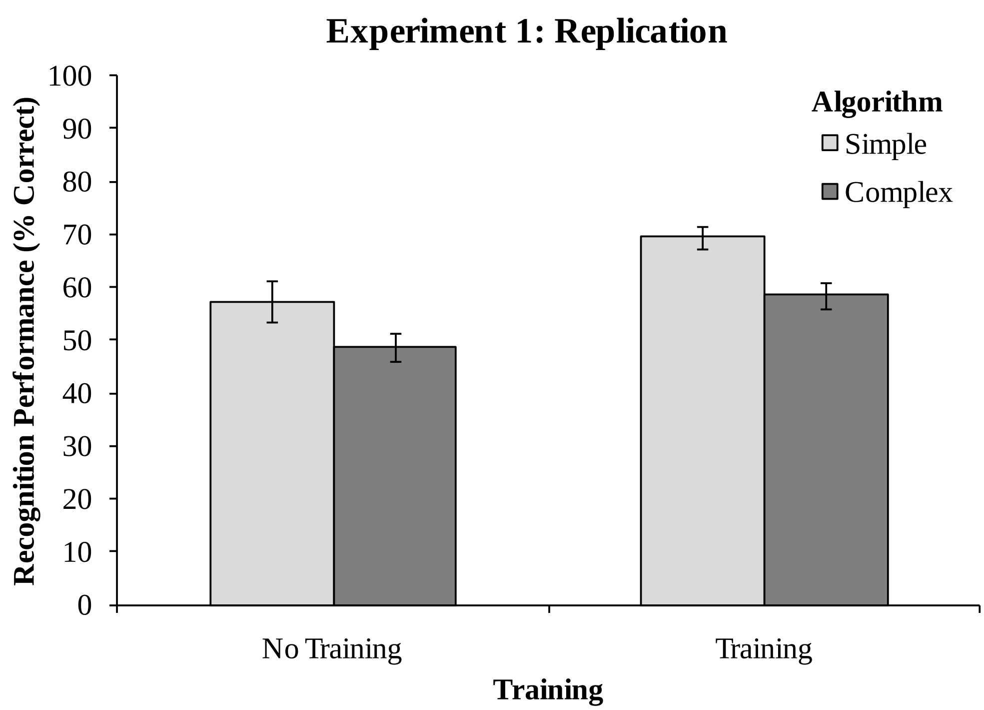


Figure 4. Graph depicting the results for Experiment 1. Mean results show recognition performance (percent correct, y axis) for the simple and complex finite state algorithms under two training conditions (training and no training, x axis). Error bars represent Standard Error.

Response Analysis. To determine whether or not training and algorithmic complexity influenced participants responses, Miss Rate, Correct Rejection Rate (CR Rate), Hit Rate, False Alarm Rate (FA Rate), Sensitivity (d’), Criterion (c), Non-parametric sensitivity (A'), and Criterion (B'D) were calculated (as shown in Table 2). A visual examination of the values for each combination of training and algorithmic complexity in Table 2 demonstrates that Hit Rate was higher for training than no training conditions, and lower for the more complex algorithm; FA rate was lower for the training condition overall and higher for the more complex algorithm. The hit rate for the training and algorithm complexity conditions was statistically significant as indicated by a between-subjects ANOVA, (training, $F(1, 36) = 0.230$, $p < 0.01$, *Partial* $\eta^2 = 0.223$; complexity, $F(1, 36) = 0.234$, $p < 0.01$, *Partial* $\eta^2 = 0.226$). Mean FA Rate was not statistically significant ($p > 0.05$). These results indicate that training significantly increased hit rate overall and that hit rate was slightly lower for the higher complexity condition. Thus, training did increase performance likely because of the exposure to the underlying pattern received during training. Furthermore, the added complexity of the patterns created by the complex FSA seems to have hindered learning of the underlying pattern resulting in a somewhat lower hit rate.

Table 2. Signal Detection Analysis of Training and Algorithm Complexity Conditions.

Algorithm	Training	Miss Rate	CR Rate	Hit Rate	FA Rate	d'	C	A'	B'D
Simple	None	0.549	0.439	0.568	0.432	0.302	0.025	0.594	0.034
	Training	0.718	0.282	0.673	0.327	0.969	-0.222	0.710	-0.264
Complex	None	0.414	0.586	0.520	0.480	-0.173	0.121	0.464	0.110
	Training	0.548	0.452	0.625	0.375	0.511	0.127	0.643	0.138

Note. CR= Correct Rejection, FA= False Alarm

Table 2 also shows the results from the d prime analysis. D prime measures the sensitivity of correctly recognizing "structured" vs. "unstructured" sequences presented in the test phase of the experiment. Sensitivity (d') was highest after training with the simple algorithm and lowest for the complex with training condition and lower for the no training condition especially for the complex algorithm. Generally, training increased sensitivity to the underlying pattern and complexity decreased sensitivity. D prime for the training and algorithm complexity conditions individually was also statistically significant as indicated by a between-subjects ANOVA, (training, $F (1, 36) = 9.267$, $p < 0.01$, Partial $\eta^2 = 0.205$; complexity, $F (1, 36) = 4.420$, $p < 0.05$, Partial $\eta^2 = 0.109$).Criterion was also calculated to examine response bias. As shown in Table 2, criterion was generally stable for the complex algorithm condition across the training conditions but lowest for the simple algorithm, with training condition. There was no statistical difference across the conditions for criterion.

Also depicted in Table 2 are non-parametric measures of sensitivity and criterion, namely A' and A'B. A prime represents the area under the Receiver Operating Characteristics (ROC) curve and corrects for non-normal signal and noise distributions. A' indicates that with values less than 0.5 that signal cannot be distinguished from noise (Stanislaw & Todorov, 1999). The non-parametric measures of sensitivity and criterion generally followed the same trends as their non-parametric counterparts (d' and c). Non-parametric sensitivity was significantly different for both training and complexity as indicated by a between-subjects ANOVA, (training, $F(1, 36) = 9.837$, $p < 0.01$, Partial $\eta^2 = 0.215$; complexity, $F(1, 36) = 4.356$, $p < 0.05$, Partial $\eta^2 = 0.108$). The non-parametric measure of criterion was not statistically different across the training and algorithmic complexity conditions ($p > 0.05$).

Overall, the response analysis indicates that the simple algorithm was likely much easier for participants to learn which enabled the participants' ability to recognize the structured stimuli at test. Additionally, participants who received training demonstrated significantly higher ability to recognize structured sequences. The effect of training on participants responding was greater for the simple sequences than for the complex sequences. These results are similar to the findings of the percent correct analysis in that performance generally was greater for training than for participants who did not receive training and for the participants who received sequences generated by the Simple FSA in comparison to the Complex FSA.

After completion of the test phase, all participants were asked to report the information that they used to make the yes/no judgments on the task. The majority of participants responded with non-representative rules that they were using to recognize the structured patterns such as using the left-right locations of the objects (which was random) and the colors of the objects. Specifically, a few participants reported at least one rule that could have been consistent with the sequences and consisted of statements such as "I used the objects that were repeating" or "I used the kinds of objects and the colors of objects". A few participants mentioned naming the objects as they encountered them. When asked how they felt on a yes decision, many participants reported the decision as "feeling right" or "feeling weird" and one even used the description that the decision “felt like intuition”. These types of responses are consistent with the literature on both intuitive decision making in simulated real-world environments (Patterson et al., 2009) and the literature on artificial grammar learning (Reber, 1967, Reber & Allen, 1978) and are considered in this experiment to be indicators of implicit learning.

Summary

One goal of this experiment was to connect with previous literature (Patterson et al., 2009) and investigate whether the general paradigm used in subsequent experiments would be capable of inducing implicit learning in an unsupervised learning paradigm with naturalistic stimuli presented within a simulated, real-world environment. The results of this experiment indicate that participants who received training demonstrated implicit learning when compared to participants who did not receive training. A second goal of this experiment was to determine specifically whether the complex algorithm could induce a level of implicit learning that would enable the issue of the diversity of exemplars to be examined. It was found that the more complex algorithm did induce implicit learning although the level of learning was lower relative to that of the learning that occurred with the simple algorithm. This result indicates that more training may be required to create comparable learning with the complex algorithm. The result that learning can occur with the complex algorithm enabled the subsequent experiment to be conducted to determine the effects of diversity of exemplars on implicit learning.

4 Experiment 2. Diversity of Exemplars for Implicit Learning

The purpose of the second experiment was to examine the relationship between the diversity and repetition of exemplars experienced during training and which lead to implicit learning. Specifically, the goal of the present experiment was to determine the effects of different combinations of diversity of exemplars and the number of repetitions of exemplars on creating robust implicit learning. Robust implicit learning as defined here was indicated by participants' learning of the underlying pattern inherent to the artificial grammar with a minimal number of repetitions. The general assumption that motivated this experiment was that there is typically an optimal combination of repetition and diversity of experience required for learning. Here, diversity/breadth was operationally defined as the total number of novel sequences presented during training. Additionally, repetition was defined as the number of presentations of individual episodes/exemplars during training. These variables were combined in this evaluation to determine their associated effect on implicit learning.

The ability to implicitly learn the underlying statistical patterns inherent within a set of stimuli, generated using a finite state algorithm, has been demonstrated using the following types of strings of stimuli: letters (Reber, 1967; 1969; 1989); symbols (Pothos, Chater, & Ziori, 2006); and more recently sequences of 3-dimensional objects (e.g. vehicles) positioned on a terrain and viewed in an dynamic, simulated, real-world environment (Patterson et al., 2009). Due to the ability to implicitly learn with many different stimuli types and in both non-realistic and simulated environments, implicit learning is considered to be a primitive form of learning which can occur under many different conditions and with many different types of stimuli. Although the ability to learn stimuli implicitly without full awareness has been demonstrated in the literature, there have not been any investigations that have endeavored to determine the diversity conditions under which rapid and robust implicit learning occurs.

Typically, the design of implicit learning experiments revolves around a fixed number of exemplars and a fixed repetition of exemplars. One of example of this is given by Patterson et al. (2009) as they used 18 exemplars repeated a total of 16 times during training. This situation does serve to create implicit learning; however, it is also of interest to determine whether increasing the number of exemplars to which a participant is exposed, increases the level at which they implicitly learn the underlying pattern because exposing participants to more exemplars exposes them to more of the underlying pattern. In this investigation, the number of exposures and the number of repetitions were combined in order to examine how the two together impact the participants' ability to form a non-analytical category of the underlying statistical pattern.

As discussed in the introduction, implicitly learned information is likely stored in a form of non-analytical category. Thus, in this investigation, an effort was made to determine the combined effects of diversity of exemplars and repetition of exemplars on the ability to represent information that has been implicitly learned. It was predicted that when participants learn the underlying pattern inherent to the structured sequences that they are abstracting information from the sequences which is likely incorporated into a prototype or into a mixed representation. Thus, it seems reasonable to conjecture that in the current experiments, participants' create a category for the information that they are abstracting from the episodes. Thus, here the learning that occurs will be considered within the framework of categorization.

Based on previous work in categorization and prototype abstraction (Homa & Vosburgh, 1976) it was predicted that in the current experiment, a greater amount of diversity of exemplars will lead to more robust learning of the prototype. An exemplar, within in the current investigation, was defined as an individual exposure to an episode with a given sequence of objects. The prototype, within the context of current investigation was thus conceptualized as consisting of the underlying pattern inherent to the critical sets of sequences created by the FSAs. Additionally, it was also predicted that rapid and robust implicit learning will require less repetition when a greater amount of diversity is inherent to the set of episodes viewed by the participants.

Homa and Vosburgh (1976) examined the effects of category breadth (in the present experiment labeled as diversity) on category learning, for which category breadth was defined as the range of distortions from a prototype that can still be considered acceptable to a category. Homa and Vosburgh manipulated category breadth by comparing learning from groups who received mixed category learning experience consisting of small, medium and large deviations from a prototype to only small deviations of a prototype. Homa and Vosburgh found that as category size increased, the percent correct for identification of category membership increased for each distortion level as a function of category size (3, 6 and 9 members of a category).

When the results from Homa and Vosburgh (1976) are considered within the context of the current experiment, it seems reasonable to conjecture that if individual exposures to the artificial grammar strings are considered as exposures to exemplars and participants are assumed to be abstracting statistical information from each string and storing it as a prototype, then the results from Homa and Vosburgh (1976) should be applicable to implicit learning with artificial grammars. Furthermore, it was also be expected that in accordance with Homa and Vosburgh (1976) that the larger diversity (or breadth) of exemplars to which a participant is exposed would lead to greater learning and higher performance at test.

When considering implicit learning in this context, the presentation of higher levels of diversity of exemplars from the FSA could be thought of as large deviations from the prototype. This experiment was designed to explore whether a combination of diversity of exemplars and repetition of experience exists which will serve to create maximum robust learning. Based on the findings of Homa and Vosburgh (1976) it was predicted that seeing more exemplars, here considered as a higher level of diversity, will lead to better implicit learning of the patterns inherent to the artificial grammar compared to a less diverse set of exemplars.

The second question that this experiment was designed to address is whether an optimal combination exists between diversity of exemplars and repetition of individual sub-sets of the sequences of vehicles that will serve to create robust implicit learning. To create maximum robust learning, there is likely a combination of diversity of exemplars and the number of repetitions that a participant receives which will lead to optimal performance. This combination would both increase the strength of the memory trace through repetition and provide sufficient coverage of the pattern to enable participants to learn the underlying structure. As in the majority of standard training paradigms, a certain amount of repetition is required for even baseline levels of task performance. Though repetition is not explored separately in this experiment, it still remains necessary to determine what combination of diversity and repetition is required in order to learn the underlying pattern inherent to the episodes. Further, though repetition could be said to improve the memory of a given exemplar, it was also predicted that if the participant does not receive enough diverse exemplars this would result in a deficiency of exposure to the sequences of objects from which to abstract the underlying pattern.

In this experiment, five levels of diversity and repetition were used as well as a control condition in which no training was received. The dependent variable was the recognition percent correct from the test phase. There were two phases in this experiment; the training phase and the test phase. The two phases were repeated twice to maximize learning outcomes and performance.

Methods

Participants. Sixty participants (18 males and 42 females, Mean age 18.76 years, S.D. 1.456) were recruited from the Psychology Participant pool at the Arizona State University Tempe campus. All participants had approximately normal vision, provided informed consent and were compensated with credit hours through the Psychology Department Participant Pool.

Stimuli. The information about the stimuli for this experiment is detailed in the general methods. Only the aspects which differ will be outlined here. The aspects which differ are the FSA that will be used, the number of sequences and the number of repetitions of each sequence.

The bottom portion of Figure 3 depicts a schematic of the complex FSA used for this experiment. A set of alternate quasi-random vehicular sequences was also produced (with the same five carrier objects) for use in the test phase of the experiment. The procedure for production of the quasi-random strings is detailed in the general method.

Procedure. Participants were randomly assigned to one of six groups. Out of the six groups of participants, five groups received both training and test phases (diversity groups), and the other group only received the test phase. Appendix A lists instructions for all phases.

Training Phase. Five groups of participants were selected to complete the training phase. The training phase consisted of a random sample of sequences taken out of the sequences generated by the FSA. The number of sequences varied dependent on the diversity condition. The diversity conditions included 3 novel exemplars repeated 48 times (Group 1), 6 novel exemplars repeated 48 times (Group 2), 12 novel exemplars repeated 24 times (Group 3), 24 novel exemplars repeated 12 times (Group 4), and 48 novel exemplars repeated 6 times (Group 5). The number of exemplars within a block also varied dependent on the diversity condition. Group 1 received one novel exemplar per block, Group 2 received 1 novel exemplar in two blocks and 2 novel exemplars in 2 blocks (number of exemplars per block was counterbalanced across participants), Group 3 received 3 novel exemplars per block, Group 4 received 6 novel exemplars per block, and Group 5 received 12 novel exemplars per block. Exemplars were presented in a fixed order and repeated across the order. Appendix C lists the sequence sets from the complex FSA. Following the procedures outlined in the general method, participants were asked to passively observe the individual episodes.

Test Phase. All participants received a test phase. All test procedures were the same as described in the general method. Groups 1-5 received the training episodes twice separated by two novel test conditions to maximize learning outcomes.

Results

Responses for all participants were scored according to the approach described in the general method. Percent correct scores were then averaged to create group means for each condition. Figure 5 depicts group mean recognition performance in percent correct (y axis) as a function of the diversity and repetition conditions (x axis) for the two training and test sessions (light and dark bars). Note that the first test session generally did not produce any performance differences. A between-subjects ANOVA found that diversity did not increase performance in the first test session $F(5, 54) = 2.059$, $p = 0.085$.

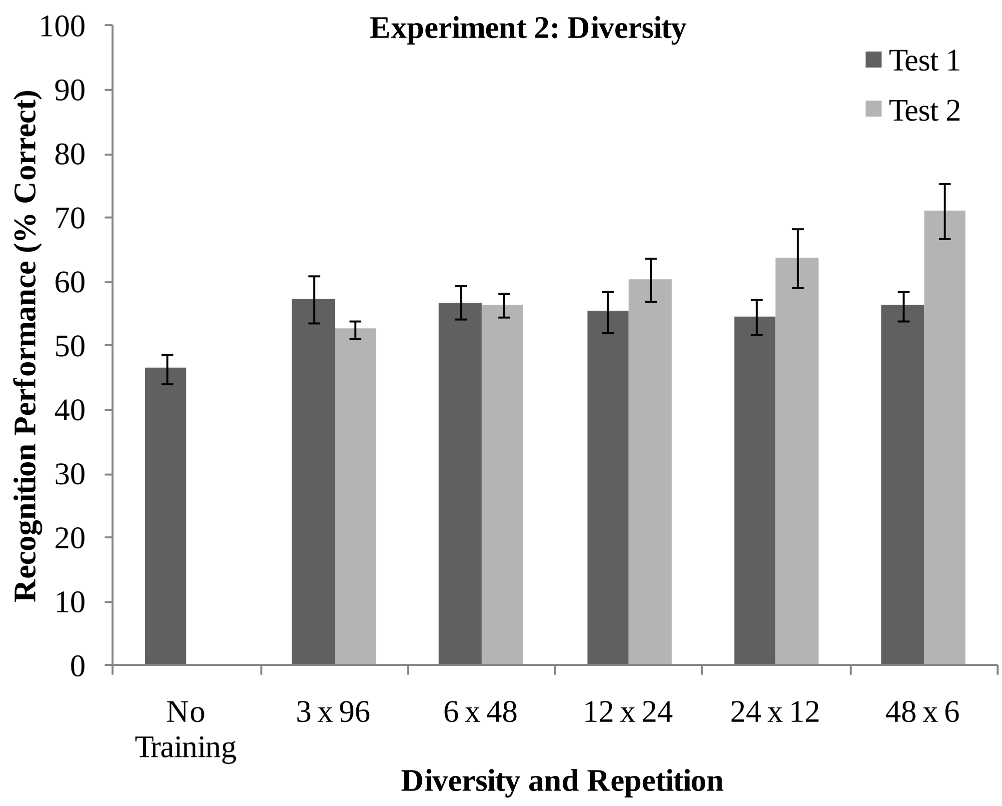


Figure 5. Graph depicting the results for Experiment 2. Mean results show recognition performance (percent correct, y axis) for no training and exemplar diversity and repetition conditions for both test sessions. Error bars represent Standard Error of the Mean. Each bar contains data from ten participants

However, Figure 5 also demonstrates that when participants completed a second training and test session, the effects of diversity on performance begin to manifest. Due to the lack of a diversity effect on implicit learning in the first training and test session, these data were not included in the final analysis. The difference in recognition performance across the first and second test sessions increased as a function of diversity (3 x 96 condition *M* difference= 4.77, 6 x 48 condition *M* difference= 0.47, 12 x 24 condition *M* difference= 5.11, 24 x 12 *M* Difference= 9.20, 48x6 condition *M* difference = 14.65). A between-subjects ANOVA found that the main effect of diversity was significant across the two test sessions, $F(5, 54) = 3.30$, $p < 0.01$ (*partial* $\eta^2 = 0.234$)

To evaluate whether Training increased performance when compared to the No Training condition, *t*-tests were computed comparing performance within each combination of Diversity and Repetition to chance performance (50%). The results from these *t*-tests are shown in Table 3. All conditions, except for No Training and 3 x 96 conditions, demonstrated performance significantly above chance. The non-significant difference between No Training and chance performance was predicted based on the results of the complex algorithm, no training group in Experiment 1, as well as the findings of Patterson et al. (2009). This result shows that for conditions with performance above chance that training was effective in producing implicit learning of the underlying pattern. The below chance performance found for the lowest diversity level was likely due to participants receiving three exemplars repeated 96 times and demonstrates that the lowest level of diversity did not provide enough coverage of the underlying pattern during training to enable above chance performance during test.

Table 3. Results from t-tests for no training and diversity and repetition conditions.

Condition	*T*	*p* (2-tailed)	*M* Difference	95% CI
No Training	-1.503	0.167	-3.523	[-8.825, 1.779]
3 x 96	1.928	0.086	2.614	[-0.453, 5.68]
6 x 48	3.441	0.007*	6.364	[2.179, 10.547]
12 x 24	3.13	0.012*	10.455	[2.899, 18.011]
24 x 12	2.898	0.018*	13.751	[3.017, 24.483]
48 x 6	4.939	0.001*	21.023	[11.395, 30.651]

Note: CI= Confidence Interval, Degrees of freedom for each test=9, $*p < 0.05$.

Recall, it was predicted that because increased diversity of exemplars provides more exposure to the underlying pattern, as diversity was increased performance would also increase. This prediction is in accordance with the results of Homa and Vosburgh (1976) who found that as breadth of categories is increased, performance also increased. As shown in Figure 5, performance was overall higher generally with training than without. Performance also appears to increase linearly with the increase in diversity.

A between-subjects ANOVA was conducted to examine whether the increase in diversity significantly increased performance. This analysis shows that the main effect of diversity was significant, $F(5, 54) = 7.137$, $p < 0.001$ (*partial* $\eta^2 = 0.398$). A Tukey's Honestly Significant Difference (HSD) *post hoc* test found significant differences between the no training condition and the 48 x 6, 24 x 12, and 12 x 24 diversity conditions) and the 48 x 6 diversity condition and the 3 x 96, 6 x 48, and 24 x 12, exemplar diversity conditions (all Tukey's HSD $p < 0.05$).

Response Analysis. To determine whether or not increases in diversity influenced participants responses, Miss Rate, Correct Rejection Rate (CR Rate), Hit Rate, False Alarm Rate (FA Rate), Sensitivity (d'), Criterion (c), Non-parametric sensitivity (A'), and Criterion (B'D) were calculated(as shown in Table 4). The values in Table 4, demonstrate that miss rate decreased as a function of diversity, correct rejections increased as a function of diversity, hit rate increased as a function of diversity, and false alarm rate did not vary with diversity. These results indicate that as the coverage of the underlying structure increases as a function of diversity, the number of hits and correct rejections also increases and the miss rate decreases. The increase in hit rate was statistically significant as indicated by a between-subject ANOVA, F(5, 54) = 8.381, $p<$ 0.001, (*partial* $\eta^2 = 0.437$).

Table 4. Signal Detection Analysis of no training and diversity and repetition conditions.

Condition	Miss Rate	CR Rate	Hit Rate	FA Rate	d'	c	A'	B'D
No Training	0.611	0.541	0.389	0.459	-0.171	0.213	0.401	0.192
3 x 96	0.673	0.725	0.327	0.275	0.185	0.499	0.536	0.523
6 x 48	0.402	0.530	0.598	0.470	0.308	0.093	0.553	-0.090
12 x 24	0.434	0.643	0.566	0.357	0.559	0.118	0.598	0.007
24 x 12	0.330	0.600	0.670	0.400	0.740	0.088	0.618	0.034
48 x 6	0.211	0.632	0.789	0.368	1.208	-0.236	0.701	-0.347

Note. CR= Correct Rejection, FA= False Alarm

Also depicted in Table 4 are the results from the d prime analysis. D prime values increased as a function of diversity indicating that as increased diversity led to increased sensitivity to structured patterns and decreased false alarm rates. This effect was also statistically significant as indicated by a between-subjects

ANOVA ($F(5, 54) = 6.242$, $p < 0.001$, (*partial* $\eta^2 = 0.366$)). Criterion was also calculated to examine response bias with increases in diversity. The criterion decreased with increases in diversity with the exception of the highest diversity condition in which the criterion shifted towards participants being generally more likely to say yes ($F(5, 54) = 2.412$, $p < 0.05$, (*partial* $\eta^2 = 0.191$)).

Also depicted in Table 4 are non-parametric measures of sensitivity and criterion, namely A’ and A’B. As shown in Table 4, there was poor sensitivity for the structured sequences during the test for the no training condition, as well as for the 3 x 96 and 6 x 48 diversity conditions. Above this level, participants appear to increase in the ability to distinguish structured from quasi-random patterns during the test phase with large sensitivity increases in the highest two levels of diversity. This overall increase in sensitivity was also statistically significant as measured by a between subjects ANOVA ($F(5, 54) = 6.396$, $p < 0.001$, (*partial* $\eta^2 = 0.372$)). A non-parametric measure of criterion (B’D) was also calculated to examine response bias. Generally, the criterion significantly shifts towards participants being more likely to say yes as diversity was increased in ($F(5, 54) = 3.374$, $p < 0.01$, (*partial* $\eta^2 = 0.238$)).

After completion of the test phase, all participants were asked to report the information that they used to make the yes/no judgments on the task. The majority of participants responded with non-representative rules that they were using to recognize the structured patterns such as using the left-right locations of the objects and colors of the objects just as in Experiment 1. A few participants again reported at least one rule that was consistent with the sequences but no participants gave significant indications of explicit knowledge of the underlying structure even considering that they received two sets of training and test phases. When asked how they felt on a yes decision, many participants reported the decision as “feeling right” or feeling good” and few even used descriptions like “I followed my gut”. These types of responses are consistent with the literature on intuitive decision making in simulated, real-world environments (Patterson et al., 2009) and the literature on artificial grammar learning (Reber, 1967, Reber & Allen, 1978) and are considered here to be indicators of implicit learning.

Summary

The principal goal of this experiment was to investigate the effect of diversity of exemplars experienced during training on implicit learning and intuitive decision making. The results of this study indicate that increased diversity of experience during training enhances implicit learning and, by implication, the accuracy of intuitive (i.e., pattern-recognition-based) decision making. Experiment 3, which will be discussed next, investigated a possible contributing mechanism to implicit learning and intuitive decision making.

5 Experiment 3: Implicit Learning Mechanism Exploration

The previous experiments explored whether the paradigm used would create implicit learning (Experiment 1) and investigated the effects of diversity and repetition on the ability of participants to implicitly learn (Experiment 2). The results from these investigations demonstrate generally that 1) implicit learning can occur within a simulated real-world environment and 2) that as a result of the realistic exposure made available through the simulated real-world environment, a robust quality of implicitly learned stimuli can be created, such that the stimuli can be learned with a minimal amount of repetition. These components of robust implicit learning (learning with minimal repetition and transfer to novel stimulus sets) should enable participants to make intuitive decisions based on the knowledge that is learned implicitly in the current paradigm.

Recall that the proposed mechanism behind intuitive decision making is a form of situational pattern recognition. Situational patterns are proposed here to be learned via an implicit, perceptually-based learning process. Specifically, the situational pattern recognition process could be in accordance with template matching theories or individual feature matching (Neisser, 1967). Within the current paradigm, the form of the situational pattern recognition process has not yet been investigated. However, regardless of the form of the pattern recognition process, it should be possible to determine whether or not specific aspects of the situation are stored and thus determine the possible associated contents of those representations.

When the premises of embodiment and the results of Marsh and Glenberg are considered within the context of the current investigation, it is possible that when participants are passively flown over the object sequences during training that they are developing fluency with the sequences of object by labeling and imitating those labels using an articulatory system. If this is the case, then in the current investigation participants may be labeling the objects (e.g. Abrams, Hummer, Bradley, Truck, and Launcher) and thus simulating the neuromuscular activity of creating the labels at a level which does not directly reach awareness.

The current experiment investigated whether participants are labeling stimuli in a similar manner as demonstrated by Marsh and Glenberg. To do so, participants were allowed to learn as they normally would during training or were asked to verbally label each of the stimuli for the duration of the training phase. In the test phase, participants were asked to either tap their left and right toes in alternation, or asked to speak the phrase “da-da. The two secondary tasks at test were included to assess whether labeling was occurring by suppressing simulation or imitation of the labels. The addition of the secondary tasks should 1) enable determination of the extent to which participants are using a form of labeling during learning and attempting to imitate the labels during test and 2) whether labeling is one of the mechanisms by which representations of implicitly learned information are created. Furthermore, if labeling is indicated by lower performance after articulatory suppression, it would demonstrate a possible mechanism for implicit learning and the subsequent situational pattern recognition that underlies intuitive decision making.

A 2 x 2 factorial design was used with two levels of labeling as one between subjects variable (no labels, labels) and two levels of suppression as the other between subjects variable (toe tapping, articulation). The dependent variable was the percent correct of recognition performance in the test phase. There were two phases in the experiment; the training and the test phase.

Methods

Participants. Sixty participants (35 males and 25 females, Mean age 19.18 years, Standard Deviation 2.4) were recruited from the Arizona State University Tempe campus. All participants had approximately normal vision, provided informed consent and were compensated with credit hours through the Psychology Department Participant Pool.

Stimuli. The information about the stimuli for this experiment is detailed in the general methods. Only the aspects which differ will be outlined here. The structured set of training episodes was used from the simple FSA shown in the top portion of Figure 3. A set of alternate quasi-random vehicular sequences was also produced (with the same five carrier objects) for use in the test phase of the experiment. The procedure for production of the quasi-random strings is detailed in the general method. The full list of both structured and quasi-random episodes is listed in Appendix C.

Procedure. Participants were randomly assigned to one of the four combinations of the label (no labels, labels) and suppression (toe tapping, articulation) conditions. Instructions for all participants for both training and test phases are listed in Appendix A. The remainder of the procedures was identical to those in the general method.

Training Phase. All training conditions are identical to Experiment 1 unless indicated. Participants assigned to the no labeling condition completed training in an unsupervised, passive manner as in the previous two experiments. Participants in the labeling condition were provided with a sheet with pictures of the five objects and their associated labels and were asked to familiarize themselves with the names of each of the objects before test (shown in Appendix B). Participants were given up to two minutes to complete this aspect of the task. They were then instructed to verbally label each of the stimuli as they were flown over them for the duration of the training phase.

Test Phase. All participants received a test phase. All procedures within the test phase were similar to those outlined in the general method, with the exception that all participants performed a secondary task during the test phase. All participants were asked to recognize structured episodes (generated from the simple FSA) from un-structured episodes (random). During the test phase, participants were instructed to either speak the phrase “da-da” or tap their toes in alternation at a rate of approximately two vocalizations or two pairs of toe alternations per second.

After the test phase was completed, each participant was asked to provide a description of the knowledge that they used during the test phase. They were also asked how they felt when they made a yes response. A subset of the no labeling participants was also asked whether or not they were naming the objects during training and to what extent they used those labels during the test phase. They were also asked to indicate what the actual labels were that they were using.

Results

Responses for all participants were scored according to the approach described in the general method. The percent correct scores were then averaged to create group means for the labeling conditions (labeling vs. no labels) and for the suppression conditions (articulation vs. toe tapping). To evaluate whether training increased performance over chance, (50%), *t*-tests were computed comparing performance within each combination of labeling and suppression to chance performance. The results for each of these tests are shown in Table 5. All combinations of conditions within the experiment demonstrated performance significantly above chance.

Table 5. Results from t- tests for labeling and suppression conditions.

Labeling	Suppression	*t*	*p*(2-tailed)	*M* Difference	95 % CI
No Labels	Toe Tapping	4.898	0.001*	20.568	[11.069, 30.067]
	Articulation	6.570	0.000*	25.227	[16.541, 33.913]
Labels	Toe Tapping	6.965	0.000*	25.000	[16.880, 33.120]
	Articulation	3.333	0.009*	14.318	[4.600, 24.037]

Note: CI= Confidence Interval, Degrees of freedom for each test=9, $*p < 0.05$.

Figure 6 depicts group mean recognition performance in percent correct (y axis) as a function of Suppression (x axis) and Labeling conditions (legend). It was predicted that verbal labeling should increase performance over that obtained when participants learn via passive, unsupervised learning. Performance was different between the No Labeling ($M = 72.424$, $SD = 12.540$) and Labeling conditions ($M = 68.052$, $SD = 12.949$). It was also predicted that there should be a difference in performance between groups who received the toe tapping and groups asked to complete the articulatory suppression during the test phase.

Performance was different between the toe tapping (M = 71.818, SD= 12.761) and Articulation conditions (M= 68.658, SD= 12.917). A 2 x 2 between-subjects ANOVA for the Experiment 3 data found that overall, having participants verbally label the stimuli did not significantly affect performance (F(1, 56) = 1.846, p = 0.180. Additionally, there was not a significant difference between the toe tapping and articulatory suppression conditions (F(1, 56) = 0.964, p = 0.330) thus, suppression did not overall decrease performance as was predicted.

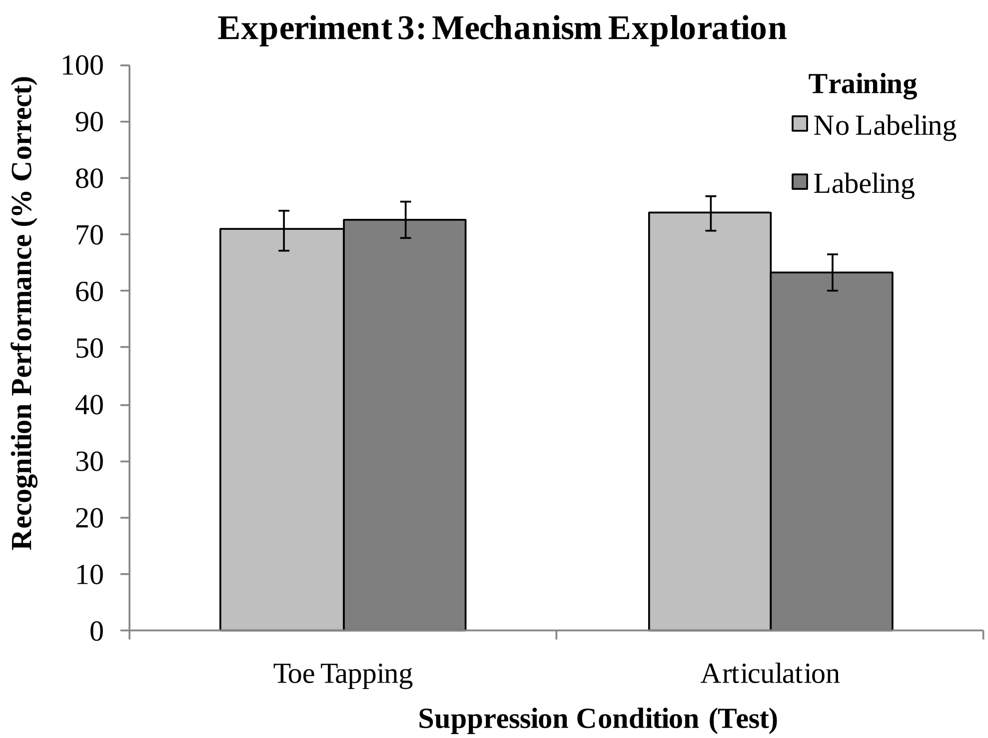


Figure 6. Graph depicting results from Experiment 3. Results show Mean recognition performance in percent correct (y axis) as a function of the Suppression Condition (x axis) and the Labeling Condition (legend). Errors bars represent Standard Error of the Mean. Each bar contains data from fifteen participants.

There was, however, a significant interaction between the suppression and labeling conditions (F(1, 56) = 3.700, p=0.059, partial η^2= 0.062). The interaction is in accordance with the prediction that articulatory suppression should act to suppress the ability of participants to use the verbal and neuromuscular labels created during the training phase and thus would act to decrease performance. This difference was significant and had a small effect size however, planned, simple contrasts comparing the With Labels and Articulation group to all others revealed significant differences between the No Labels and Toe Tapping group and the Labels and Articulation group (Difference = 10.562, p = 0.024), as well as the With Labels, Toe Tapping group and the With Labels and Articulation group (Difference = 9.350, p = 0.045). Thus, suppression did significantly decrease performance over that of unsuppressed levels of performance for the verbal labeling group. If interpreted in the context of Figure 9, it appears that though articulatory suppression did not act to suppress performance when participants were allowed to learn in a passive, unsupervised manner, suppression did appear to decrease performance when participants were asked to verbally label the stimuli in the training phase and then perform articulatory suppression during the test phase.

Response Analysis. To determine whether or not labeling and suppression influenced participants responses, Miss Rate, Correct Rejection Rate (CR Rate), Hit Rate, False Alarm Rate (FA Rate), Sensitivity (d'), Criterion (c), Non-parametric sensitivity (A'), and Criterion (B'D) were calculated (as shown in Table 6). A visual examination of the mean values in Table 6 demonstrates that Mean Hit Rate was generally stable for the no labeling condition and for the labeling with toe tapping conditions, however, when participants performed articulatory suppression at test after labeling mean hit rate decreased. Mean FA Rate was also relatively similar across all conditions except for the labeling, articulatory suppression condition. There were no differences for either Hit Rate or FA Rate across the conditions as assessed by between-subjects ANOVAs (all $p > 0.05$).

Table 6. Signal Detection Analysis of Labeling and Suppression Conditions.

Labels	Suppression	Miss Rate	CR Rate	Hit Rate	FA Rate	d'	c	A'	B'D
None	Toe Tapping	0.262	0.718	0.738	0.282	1.894	-0.306	0.794	-0.217
	Articulation	0.274	0.753	0.726	0.247	1.527	0.017	0.812	0.014
Labels	Toe Tapping	0.265	0.720	0.735	0.280`	1.340	-0.028	0.796	-0.048
	Articulation	0.342	0.609	0.658	0.391	0.807	-0.060	0.693	0.024

Note. CR= Correct Rejection, FA= False Alarm

Sensitivity (d') was overall lower for the two articulatory suppression conditions but lowest for the with-labeling condition. There was a significant difference in the sensitivity of the labeling conditions ($F(1, 56) = 4.443$, $p < 0.05$). Criterion was lowest for the no labels toe tapping condition, followed by the labeling and articulatory suppression condition, and the labeling, toe tapping condition and the no labeling and articulation condition. The difference in criterion across conditions was not statistically significant. These results indicate that generally participants had a harder time recognizing the structured patterns during the test phase especially for the labeling and articulatory suppression condition.

After test phase completion, all participants were asked to report the information that they used to make the yes/no judgments. As in the previous two experiments, the majority of participants responded with non-representative rules that they were using to recognize the structured patterns such as using the left-right locations of the objects and colors of the objects. For the no-labeling condition, a few participants again reported at least one rule consistent with the sequences, but no participants gave significant indications of explicit knowledge of the underlying structure. For the labeling condition, there were more statements that were consistent with actually learning the underlying patterns; this may have been aided by having participants label the objects during training. Even though there were more statements consistent with the underlying patterns, there were still not more than one or two beyond the no-labeling group. This result was thus interpreted as an indicator of implicit learning of the patterns.

A subset of the participants in the no labeling group (ten participants out of thirty) was also asked whether or not they were naming or labeling the objects during the training phase. The majority of the participants asked about labels stated they were labeling, using the labels on more than half of the test trials, and gave labels analogous to the actual vehicle names. Finally, when asked how they felt on a yes decision, many participants reported the decision as “feeling right” or feeling good” and few even used descriptions like “I followed my gut”. These types of responses are consistent with the literature on both intuitive decision making in simulated real-world environments (Patterson et al., 2009) and the literature on artificial grammar learning (Reber, 1967, Reber & Allen, 1978) and are considered here to be indicators of implicit learning.

Summary

This principle goal of this experiment was to investigate evidence for a possible embodied-mechanism contribution to the explanation for implicit learning and intuitive decision making. The results of this experiment suggest that labeling (as evidenced by decreased performance with articulatory suppression) is one possible mechanism contributing to the implicit learning of statistical patterns. This result, together with the results from Experiments 1 and 2, will be discussed in the next section.

6 Discussion

The principal results of this investigation demonstrate, in general, that implicit learning (a route to the development of intuitive decision making) can occur within a simulated real-world environment involving complex, naturalistic stimuli. Moreover, the current results suggest that the diversity of experience is an influential factor in the development of implicit learning because it increases coverage of the associations embedded within the situational patterns. Finally, the results suggest that an embodied mechanism, namely labeling, can partially account for the implicit learning found in this investigation. Taken in concert, the results of this investigation have revealed several key factors that play an important role in the development of intuitive decision making.

In Experiment 1, it was shown that, consistent with Patterson et al. (2009), participants were able to learn situational patterns (i.e. object sequences) implicitly in a simulated real-world environment. Implicit learning is thought to provide a route by which intuitive decision making is developed (Hogarth, 2001; Reber, 1989; Patterson et al., 2009). The keystone of intuitive decision making is the ability to recognize situational patterns which is likely based on non-analytical category formation created from implicit learning (Brooks, 1978; Brooks & Vokey, 1991; Raab & Johnson, 2008). The results of Experiment 1 substantiate the claim that implicit learning enables the development of the situational pattern-recognition process which underlies intuitive decision making.

Experiment 1 also explored whether implicit learning could occur with a more complex algorithm. It was found that implicit learning did occur using the more complex algorithm, however, the level of learning with the complex algorithm was significantly lower (but still above chance level) than the learning that occurred with the simple algorithm. Nonetheless, it is inferred here that implicit learning can provide a foundation for intuitive decision making even when the patterns to be learned are complex.

In Experiment 2, it was shown that increased diversity of experience during training enhances the accuracy of intuitive decision making and, by implication, increased diversity enhances implicit learning. It is likely that diversity is influential because exposure to a greater number of exemplars increases the chances for individuals to come into contact with more of the associations comprising the situational pattern (i.e. greater coverage) which, in turn, can reinforce learning. Reinforced learning, though greater coverage of the underlying patterns, should facilitate the establishment of a stronger memory representation of the pattern. This explanation is consistent with the findings of Homa and Vosburgh (1976), who revealed that exposure to a mixture of small, medium and large deviations from a prototype, enhances one's ability to identify category members in comparison to exposure to only small deviations from a prototype. In the future, this result could be extended by an investigation of the relationships among diversity of experience, algorithmic complexity, and implicit learning. Based on the results of this set of experiments, I would predict that, as complexity is increased, diversity would also need to be increased in order to create comparable levels of implicit learning.

Learning in conditions of increased diversity was less prone to errors, fostered increased sensitivity to the underlying structure, and produced a balanced response criterion. These results are taken as evidence that increases in diversity not only increased correct responding but also increased sensitivity to the structured patterns during the recognition test, essentially demonstrating more robust learning and thus resulting in robust intuitive decision making. Recall from the introduction that robust intuitive decision making would be indicated here by learning which occurred with minimal repetition of stimuli. In this investigation, the minimal repetition of stimuli, together with more diversity, led to an implicitly learned representation of the structure of the underlying pattern and thus led to more robust intuitive decision making.

The results of this investigation demonstrate that diversity of experience significantly enhances implicit learning and suggest that the formation of an enhanced memory representation can lead to increased transfer of learning to novel exemplars (i.e., the novel exemplars during test). From this result, I conjecture that diversity calibrates the learning process to the extent that the more diversity of exposure to the underlying patterns within an environment; the more complete the resulting representation of the patterns in memory. In this investigation, it is likely that a more complete memory representation of the underlying patterns led to increased performance, as demonstrated by the increase in sensitivity and stability of decision making as diversity was increased. This more complete representation of the underlying patterns may have been contributed to both by the diversity of the patterns as well as the two training and test sessions that participants received. Due to the two cycles of training and test, in the second cycle participants are familiar with the general procedures used in the experiment. Specifically, participants are aware that there is an underlying pattern and they know that they will be tested on it. By definition the procedure itself is no longer implicit. However, participants were still not able to explicitly define the underlying pattern even after the second test. The ability to explicitly define the underlying pattern has been considered by many to be a main indicator of implicit learning (Reber, 1967; Patterson et al., 2009). Thus, this result will be interpreted in the current investigation as still indicating that the learning is still of a level that does not reach conscious awareness and is still considered to be largely implicit.

In Experiment 3, it was shown that labeling, by itself, did not increase implicit learning and suppression, by itself, did not decrease implicit learning. However, when participants were asked to label the stimuli verbally during training and then asked to perform articulatory suppression during the recognition test, suppression decreased performance. This finding is in accordance with the prediction that verbal labeling is one means by which participants learn the relations within the underlying pattern inherent in the set of object sequences. Moreover, this finding is also consistent with the prediction that articulatory suppression after verbal labeling would act to suppress recall of the labels assigned to those relations, which resulted in decreased performance. Thus, the results of Experiment 3 suggests that labeling is one possible mechanism for implicit learning, and thus the development of intuitive decision making, within the simulated real-world environment used in the current investigation.

The proposal that verbal labeling is one possible mechanism underlying the implicit learning in the present investigation is in accordance with the grounded perceptual-symbol system hypothesis proposed by Barsalou (2009). According to this hypothesis, verbal (or even subvocal) labels are created as a means of coupling the experience in the environment, the memory of the experience in that environment, and relevant perceptual variables, which serves to ground the learning. According to this hypothesis, in this study, as participants experienced sequences of objects while undergoing simulated flight over the terrain, the participants were creating a memory representation that not only contained perceptual information about the simulated environment but which also contained the verbal labels for the vehicles and the transitions between the labels.

Neuromuscular labels as explored in the current investigation need not be verbally or subvocally grounded. The type of label created for a specific task would be contingent on the interaction completed in the task. As an example, if participants were also asked to control their locomotion, they may also embed in their neuromuscular representations of the task, a motorically-driven representation. The interactions between the types of labels represented as a function of the elements present within a task and the associated embodied representation of the task will be investigated in future research.

The suggestion that, after labeling the stimuli during training, articulatory suppression acted to suppress the participants' ability to imitate the labels during test is in accordance with the embodied statistical learning account of Marsh and Glenberg (2010). Recall that Marsh and Glenberg proposed that participants learn underlying patterns via a form of neuromuscular labeling whereby the participants are subvocally labeling stimuli during training and then imitating the labels during test. Furthermore, they found that performance after learning can be suppressed by having participants perform a task which inhibits the ability to imitate or simulate the labels created during training. Marsh and Glenberg used a paradigm similar to that reported here with the exception that the structured sequences used by Marsh and Glenberg were composed of auditory (tones) and visual patterns (boxes). The findings from the current study, if interpreted in light of Marsh and Glenberg, suggests a conclusion that one possible contributing mechanism underlying implicit learning and intuitive decision making is likely an embodied form of learning directly linked to the interaction with the information within an environment.

The finding that suppression did not affect individuals who were not asked to label could be because these individuals learned the relationships embedded within the patterns through a different process. This could also be the reason that labeling alone did not act to significantly increase performance in the current investigation. Future research should explore what other possible mechanisms underlie implicit learning in our simulated real-world environment.

Across the three experiments reported here, the highest level of recognition performance was on the order of 70 to 75% correct. This result raises the question of why performance saturated at this level and what could be done in the future to elevate performance above that level. There are a number of interacting factors that should determine the level of performance within this implicit learning paradigm, such as the total number of training trials, algorithmic complexity, and the presence or absence of feedback.

First, the number of training trials in the current investigation was 288, and this number of training trials was used because it induced sufficient levels of implicit learning without being onerous to the participants running in the experiments. It would be expected that a greater number of training trials would elevate learning to a higher level than that shown here, but the time commitment on the part of the participants would be greater. Second, the two levels of algorithmic complexity used in the current investigation were chosen based on previous research (Patterson, et al., 2009) and enabled the manipulation of diversity in Experiment 2. It would be expected that a simpler algorithm would produce higher levels of learning, but it would not generate a sufficient number of exemplars for examining diversity. Third, participants were not provided any feedback in order to simulate the kind of learning that occurs in many naturalistic contexts. It would be expected that feedback would elevate learning to a higher level than that found here but the presence of feedback would make the paradigm generalize less to those naturalistic contexts.

Implicit learning is considered here, and by Patterson, Pierce, Bell and Klein, (2011) to be a ubiquitous form of learning that underlies and supports the acquisition of many different skills. In the current investigation, it is likely that the implicit learning was reflective of a naturally evolved, primitive ability designed to extract patterns and relationships from our environment. Implicit learning is seen here as a primitive ability as it has been found to be a process which leads to the development of tacit knowledge and procedural memory (Reber, 1989; 1993; Perruchet & Pacton, 2006) as well as providing a foundation for intuitive decision making (Evans, 2008; Patterson, et al., 2009; Patterson et al., 2011).

The current results suggest that training intuitive decision making can occur within simulated real-world environments with naturalistic stimuli and that this training could be effectively transferred to novel sequences of objects with the same underlying statistical dependencies. Across the three experiments reported here, all participants were learning implicitly within a simulated real-world environment with no instructions to learn, no instructions on where to direct attention, and no feedback. The results of the present study could be applied to the development of training regimes in many different tasks. Generally, the current results suggest that, in applied situations, it may be better to train individuals on a wide range of experiences even if that sacrifices repetition of those experiences. This wider range of experiences would lead to a more representative memory of their common elements, which should lead to increased robustness of decision making skills in natural environments with inherent complexity.

One application could be operations with Remotely Piloted Aircraft (RPAs). In RPA ground control stations, a team including a pilot and sensor operator controls one or more RPAs and performs flight control, surveillance and tactical aspects of the mission. It could be possible to train both the tasks of the pilot as well as the task of the sensor operator with the implicit learning paradigm used here. For example, a pilot in a given military operational environment might notice a drop in altitude in the video feed, combined with a change in the altimeter, followed by an engine indicator. This could mean that the pilot then needs to make a quick decision to ensure that the RPA does not crash. In the present context, this scenario might generate a pattern of cues on which the pilot might be trained using techniques analogous to the methods employed in the present investigation.

Moreover, in the case of the sensor operator, they could be sent on a mission to monitor for improvised explosive devices (IEDs). The sensor operator must integrate cues across the small field-of-view from the RPV camera, the sensors available on a given RPV (such as an infrared sensor), as well as information about the content within the camera and sensors to search for cues relating to an IED. The operator might have been informed that the area has been known to have IEDs buried in the ground, which would require the operator to monitor the ground for some sort of pattern of disturbance. The pattern recognition process underlying intuitive decision making could also be helpful in recognition of cultural aspects of a task environment. In the context of the IED task described above, it could be useful in the detection of cultural patterns in the task environment such as looking for the presence or absence of suspicious people or vehicles that could be planting an IED or who could serve as a threat. This scenario might also generate a pattern of cues on which the sensor operator might be trained using techniques analogous to the methods employed in the present investigation.

An additional example would be applied situations involving command and control, which would require the processing and integration of large amounts of dynamic tactical and strategic information by a decision maker who has to make critical decisions in a timely manner under large amounts of uncertainty and time pressure. The team leader or commander in a command and control situation must process and understand a large amount of information coming from multiple sources (such as RPVs, ground commanders, and other aircraft), maintain awareness of communication between the players in the tactical scenario, and make decisions consistent with the overall goal of the mission. Here again, this command and control scenario might generate a pattern of cues on which the team leader or commander might be trained using techniques analogous to the methods employed in the present investigation.

The results of the current investigation could also be applied to many other tasks. In the applications presented here, exposure to a diversity of patterns should lead to a memory representation of the underlying statistical dependencies and invariants within the pattern that should allow for the pattern to be transferred to novel situations with the same underlying statistical dependencies. A similar training regime based on the paradigm utilized in the current investigation could be developed for many different tasks. Development of a training regime based on the findings of the current investigation may enable crucial intuitive decisions to be made which, in some cases, could result in the saving of resources or lives.

Further research is required to determine how to apply the results of the current investigation to training applications.

In summary, the results of this investigation show that intuitive decision making can be trained within a simulated, real-world environment through the development of implicit learning. This training was accomplished with exposure to either simple or more complex situational patterns. However, if the underlying situational pattern is more complex, then an increase of diversity of exposure to the pattern is likely to be required to ensure maximum learning outcomes. Moreover, there is likely to be an embodied mechanism, namely neuromuscular labeling, which can partially account for the implicit learning and development of intuitive decision making that occurs as a result of the increased diversity.

References

Andrews, D. H. & Bell, H. H. (2000). Simulation-based training. In Tobias, S. & Fletcher, J.D. (Eds.) *Training & retraining: A handbook for business, industry, government, and the military* (pp. 357-384). American Psychological Society.

Aslin, R. N., Saffran, J. R. & Newport, E. L. (1998). Computation of conditional probability statistics by 8 month old infants. *Psychological Science*, *9*(4), 321-324. doi: 10.1111/1467-9280.00063.

Bargh, J.A. & Morsella, E. (2008). The Unconscious Mind. *Perspectives on Psychological Science*, *3*(1), 73-79. doi: 10.1111/j.1745-6916.2008.00064.

Barsalou, L. (2008). Grounded Cognition. *Annual Review of Psychology*, *59*. doi: : 10.1146/annurev.psych.59.103006.093639.

Barsalou, L. (1999). Perceptual Symbol Systems. *Behavioral and Brain Sciences, 22*, 577-660.

Boydstun, A. S., Patterson, R., Pierce, B., Park, L. M., & Shannan, J. (2010). On the development of training principles for intuitive decision making. *Proceedings of the Human Factors and Ergonomics Society 54th Annual Meeting*, San Francisco, CA, October, 2010.

Brady, T. F. & Olivia, A. (2008). Statistical learning using real-world scenes. *Psychological Science*, *19*(7), 678-685. doi: 10.1111/j.1467-9280.2008.02142.x.

Brooks, L. R. (1978). Non-analytic concept formation and memory for instances. In E. Rosch & B. Lloyd (Eds.), *Cognition and concepts* (pp. 169-211). Hillsdale, NJ: Erlbaum.

Brooks, L. R. & Vokey, J. R. (1991). Abstract Analogies and Abstracted Grammars: Comments on Reber (1989) and Mathews et al. (1989). *Journal of Experimental Psychology: General*, *120*(3), 316-323.

Evans, J. S. B. T. (2008). Dual-processing accounts of reasoning, judgment and social cognition. *Annual Review of Psychology*, *59*, 255-278. doi: 10.1146/annurev.psych.59.103006.093629.

Fiser, J. & Aslin, R.N. (2002). Statistical learning of higher-order temporal structure from visual shape sequences. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 28,* 458-467. doi: 10.1037//0278-7393.28.3.458.

Fiser, J. & Aslin, R.N. (2001). Unsupervised statistical learning of higher-order spatial structures from visual scenes. *Psychological Science, 12,* 499-504. doi: 10.1037//0278-7393.28.3.458.

Flin, R. & Mitchell, L. (Eds.) (2009). Safer Surgery: Analysing Behaviour in the Operating Theatre. Farnham: Ashgate.

Franks, J. J. & Bransford, J. D. (1971). Abstraction of visual patterns. *Journal of Experimental Psychology*, *90*(1), 65-74.

Gibson, J. J. (1977). The Theory of Affordances. In *Perceiving, Acting, and Knowing,* Eds. Robert Shaw and John Bransford, Hillsdale, NJ: Lawrence Erlbaum Associates.

Gibson, J. J. & Gibson, E. (1955). Perceptual Learning: Differentiation or enrichment? *Psychological Review*, *62*(1), 32-41.

Glenberg, A. M. (2010). Embodiment as a Unifying Perspective for Psychology. *Wiley Interdisciplinary Reviews: Cognitive Science*, 1(4), 586-596, doi:10.1002/wcs.55.

Goldstein, E. B. (2007). *Cognitive Psychology: Connecting Mind, Research and Everyday Experience.* Wadsworth Publishing

Gomez, R. L., Gerken, L., & Schvaneveldt, R. W. (2000). The basis of transfer in artificial grammar learning. *Memory & Cognition*, *28*(2), 253-263.

Heit, E. (2000). Properties of inductive reasoning. *Psychonomic Bulletin & Review, 7*(4), 569-592.

Hofstadter, D. R. (2001). Epilogue: Analogy as the Core of Cognition. In Gentner, D., Holyoak, K.J., & Kokinov (Eds.), *The analogical mind: Perspectives from cognitive science.* (pp. 499-538). Cambridge: MIT Press.

Hogarth, R. M. (2005). Deciding analytically or trusting your intuition? The advantages and disadvantages of analytic and intuitive thought. In Betsch, T. & Haberstroh, S. (Eds.), *The routines of decision making*. (pp. 67-82) Mahwah, NJ: Lawrence Erlbaum Associates.

Hogarth, R.M. (2001). *Educating intuition.* Chicago: The University of Chicago.

Holyoak, K. J., Gentner, D., Kokinov, B. N. (2001). Introduction: The place of analogy in cognition. In Gentner, D., Holyoak, K.J., & Kokinov (Eds.), *The analogical mind: Perspectives from cognitive science.* (pp. 1-19). Cambridge: MIT Press.

Homa, D. (1984). On the nature of categories. *The Psychology of Learning and Motivation*, *18*, 49-94.

Homa, D., Proulx, M. J., & Blair, M. (2008). The modulating influence of category size on the classification of exception patterns. *The Quarterly Journal of Experimental Psychology*, *61*(3), 425-443. doi: 10.1080/17470210701238883.

Homa, D. & Vosburgh, R. (1976). Category Breadth and the abstraction of prototypical information. *Journal of Experimental Psychology: Human Learning and Memory*, *2*(3), 322-330.

Kahneman, D. & Klein, G. (2009). Conditions for intuitive expertise: A failure to disagree. *American Psychologist*, *64*(6), 515-526. doi: 10.1037/a0016755.

Kahneman, D. & Tversky, A. (1979). Prospect Theory: An analysis of decision under risk. *Econometrica*, *47*(2), 263-291.

Klein, G. (2008). Naturalistic Decision Making. *Human Factors*, *50*(3), 456-460. doi: 10.1518/001872008X288385.

Klein, G. A. (1989). Recognition-primed decisions. In W.B. Rouse (Ed.), Advances in man-machine systems research (Vol. 5, pp. 47-92). Greenwich, CT: JAI Press.

Klein, G. A. (1998). Sources of power: How people make decisions. Cambridge, MA: MIT Press.

Krokhmal, P., Murphey, R., Pardalos, P., Uryasev, S. & Zrazhevsky, G. (2003). Robust Decision Making: Addressing Uncertainties in Distributions. (pp. 165-185). In S. Butenko et al (Eds.), *Cooperative Control: Models, Applications and Algorithms*. Kluwer Academic Publishers.

Lopes, L. L., & Oden, G. C. (1991). The rationality of intelligence. *Poznan Studies in the Philosophy of the Sciences and the Humanities*, *21,* 199-123.

Malt, B. C. (1989). An on-line investigation of prototype and exemplar strategies in classification. *Journal of Experimental Psychology: Learning Memory & Cognition, 15*(4), 539-555.

Marsh, E. R., & Glenberg, A. R. (2010). The Embodied Statistician. *Frontiers in Psychology*, *2*, doi:10.3389/fpsyg.2010.00184. .

Mathews, R. C., Buss R. R., Stanley, W. B., Blanchard-Fields, F., Cho, J. R., & Druhan, B. (1989). Role of implicit and explicit processes in learning from examples: A synergistic effect. *Journal of Experimental Psychology: Learning, Memory and Cognition, 15*(6), 1083-1100.

Milkman, K. L., Chugh, D. & Bazerman, M. H. (2009). How can decision making be improved? *Perspective on Psychological Science, 4*, 379-383. doi: 10.1111/j.1745-6924.2009.01142.x.

Minda, J. P. & Smith, J. D. (2001). Prototypes in category learning: the effects of category size, category structure, and stimulus complexity. *Journal of Experimental Psychology: Learning, Memory, & Cognition, 27*(3), 775-799.

Neisser, U. (1967). *Cognitive Psychology*. Appleton-Century-Crofts: New York.

Nosofsky, R. M. & Zaki, S. R. (1998). Dissociations between categorization and recognition in amnesic and normal individuals: An exemplar based interpretation. *Psychological Science, 9*(4), 247-255.

Nygren, T. E. & White, R. J. (2002). Assessing individual differences in decision making styles: Analytical vs. Intuitive. *Proceedings of the Human Factors and Ergonomics Society 46th Annual Meeting – 2002, 953-957.*

Patterson, R. E., Pierce, B. P., Bell, H., & Klein, G. (2011). Implicit Learning, Tacit Knowledge, Expertise Development, and Naturalistic Decision Making. *Journal of Cognitive Engineering and Decision Making*, 4(4), 209-303. doi: 10.1518/155534310X12895260748867.

Patterson, R., Pierce, B. P., Bell, H., Andrews, D. & Winterbottom, M. (2009). Training robust decision making in simulated real-world environments. *Journal of Cognitive Engineering and Decision Making*, *3*(4), 331-361. doi: 10.1518/155534309X12599553478836.

Perruchet, P. & Pacton, S. (2006). Implicit Learning and statistical learning: one phenomenon, two approaches. *TRENDS in Cognitive Sciences*, *10*(5), 233-238. doi:10.1016/j.tics.2006.03.006.

Posner, M. I. & Keele, S. W. (1968). On the genesis of abstract ideas. *Journal of Experimental Psychology*, *77*(3), 353-363.

Pothos, E. M., Chater, N., Ziori, E. (2006). Does stimulus appearance affect learning? *American Journal of Psychology*, *119*(2), 277-301.

Raab, M. & Johnson, J. G. (2008). Implicit learning as a means to intuitive decision making in sports (pp. 119-134). In Plessner, H., Betsch, C., &

Betsch, T.(Eds.). *Intuition in Judgement and Decision Making*. New York: Lawrence Earlbaum Associates.

Reber, A. S. (1967). Implicit Learning of artificial grammars. *Journal of verbal learning and verbal behavior.6*, (855-893).

Reber, A. S. (1969). Transfer of syntactic structure in synthetic languages. *Journal of Experimental Psychology*, *81*(1), 115-119.

Reber, A. S. (1989). Implicit Learning and Tacit Knowledge. *Journal of Experimental Psychology: General, 118*(3), 219-235.

Reber, A. S. (1993). Implicit Learning and Tacit Knowledge: An Essay on the Cognitive Unconscious. New York: Oxford University Press.

Reber, A.S. & Allen, R. (1978). Analogic and Abstraction strategies in synthetic grammar learning: A functionalist interpretation. *Cognition*, *6*, 189-221.

Reber, A.S., Kassin, S. M., Lewis, S., & Cantor, G. (1980). On the relationship between implicit and explicit modes in the learning of a complex rule structure. *Journal of Experimental Psychology: Human Learning and Memory*, 6(5), 492-502.

Rehder, B. & Hastie, R. (2004). Category coherence and category-based property induction. *Cognition*, *91*, 113-153.

Regan, H. M., Ben-Haim, Y., Langford, B., Wilson, W. G., Lundberg, P., Andelman, S. J. & Burgman, M. A. (2005). Robust decision-making under severe uncertainty for conservation management. *Ecological Applications, 15*, 1471–1477. doi:10.1890/03-5419.

Rosch, E. (1978). Principles of Categorization. In Rosch, E. & Lloyd, B.B. (Eds.). *Cognition and Categorization* (pp.27-49). Hillsdale, NJ: Lawrence Erlbaum Associates.

Shapiro, L. A. W. (2010). *Embodied Cognition*. Routledge.

Shin, H.J., & Nosofsky, R.M. (1992). Similarity scaling studies of dot pattern classification and recognition. *Journal of Experimental Psychology: General*, *121*, 278-304.

Smith, J. D. & Minda, J. P. (1998). Prototypes in the mist: the early epochs of category learning. *Journal of Experimental Psychology: Learning, Memory & Cognition, 24*(6), 1411-1436.

Turvey, M.T. (1990). Coordination. *American Psychologist*, *45*(8), 938-953.

von Neumann, J. & Morgenstern, O. (1944). *Theory of Games and Economic Behavior*. 1953 edition, Princeton, NJ: Princeton University Press.

Westcott, M. R. (1968). *Toward a contemporary psychology of intuition: a historical, theoretical, and empirical inquiry*. New York, NY: Holt, Rinehart and Winston.

Wilson, M. (2002). Six views of embodied cognition. *Psychonomic Bulletin & Review*, *9*(4), 625-636. doi: 10.3758/BF03196322.

Zsambok, C. E. & Klein, G. A. (1997). *Naturalistic Decision Making*. Mahwah, NJ: Lawrence Erlbaum Associates, Inc.

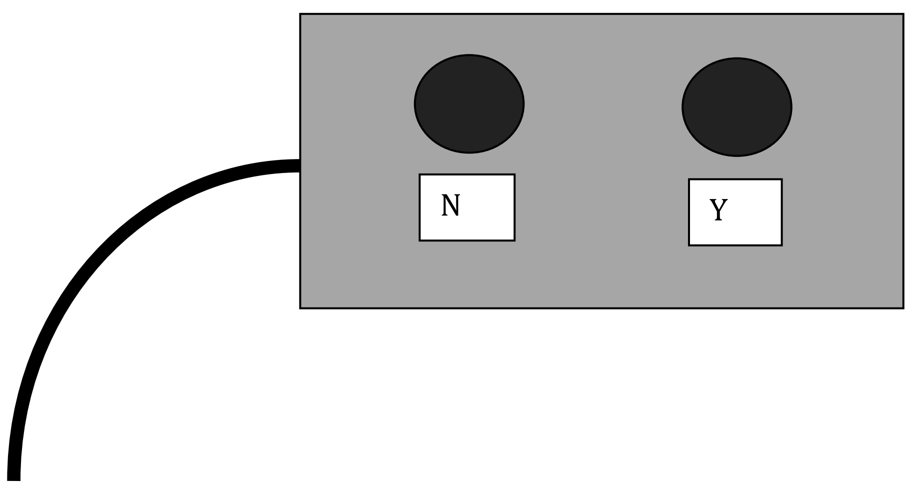
APPENDIX A

INSTRUCTIONS FOR ALL EXPERIMENTS

Decision Making Study Instructions (Training Groups Exp. 1, 2, & 3)

PLEASE TURN OFF YOUR CELL PHONE AND PUT IT AWAY! THE FOLLOWING TASK REQUIRES A HIGH LEVEL OF CONCENTRATION. A RINGING CELL PHONE WILL DISQUALIFY YOU FROM THE STUDY.

You will be seated in front of a computer display. You will be asked to view a series of objects on the screen. Please watch them and the experimenter may discuss what you have just viewed. The experiment should take approximately 45-60 minutes with scheduled breaks. If you need additional breaks, please let me experimenter know/ Once the experimenter tells you to begin, please push either button (as shown in the figure below).You will appear to be flying over a series of objects. These sequences will consist of five different objects in various orders on a desert-type terrain. Please watch them until you receive a message that all trials have been completed.

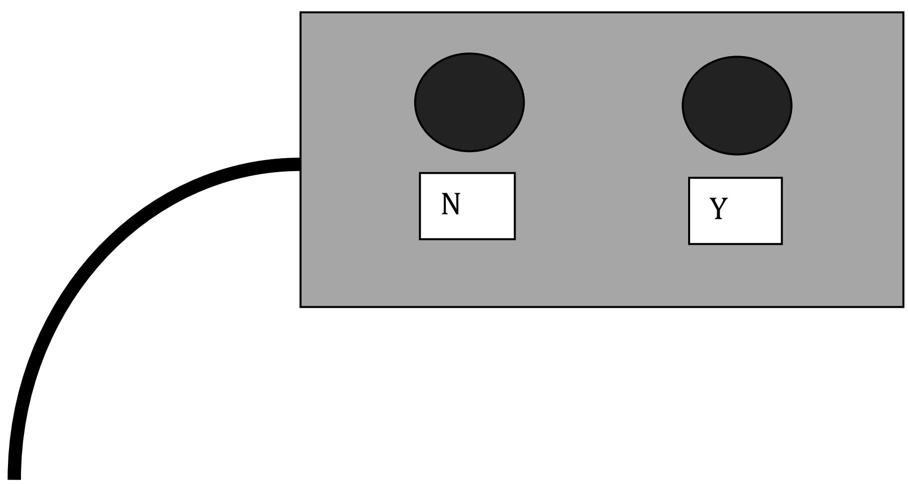


Decision Making Study Instructions: (Training Groups Exp. 1, 2 & 3)

PLEASE TURN OFF YOUR CELL PHONE AND PUT IT AWAY! THE FOLLOWING TASK REQUIRES A HIGH LEVEL OF CONCENTRATION. A RINGING CELL PHONE WILL DISQUALIFY YOU FROM THE STUDY.

Part Two

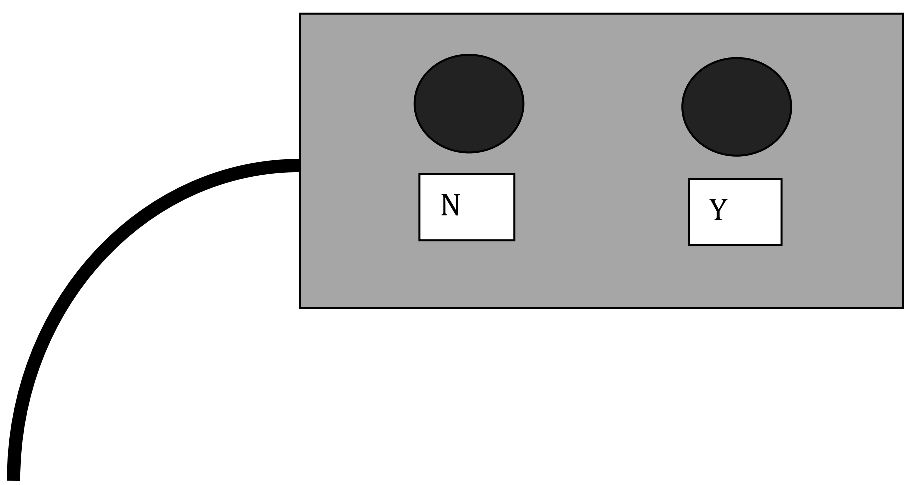
For this portion of the experiment you will again be seated in front of a computer display with a button box (See picture below). The series of objects that you just watched form a sequence which follows a specific underlying structure. For this portion of the experiment, you will be viewing the same objects you have just viewed but in sequences you have not seen before. Some of these sequences will follow the same underlying structure you saw in the previous task and some will not. Your job is to determine if the sequences follow the same underlying structure or not. If the sequence appears to have the same underlying structure, then please press the button on the button box marked “Y” for Yes. If the sequence does not follow the same underlying structure, then please press the button on the button box marked “N” for NO. You will continue to do this until you receive a message that all trials are complete.



Decision Making Study Instructions: (Test Only Groups Exp. 1 & 2)

PLEASE TURN OFF YOUR CELL PHONE AND PUT IT AWAY! THE FOLLOWING TASK REQUIRES A HIGH LEVEL OF CONCENTRATION. A RINGING CELL PHONE WILL DISQUALIFY YOU FROM THE STUDY.

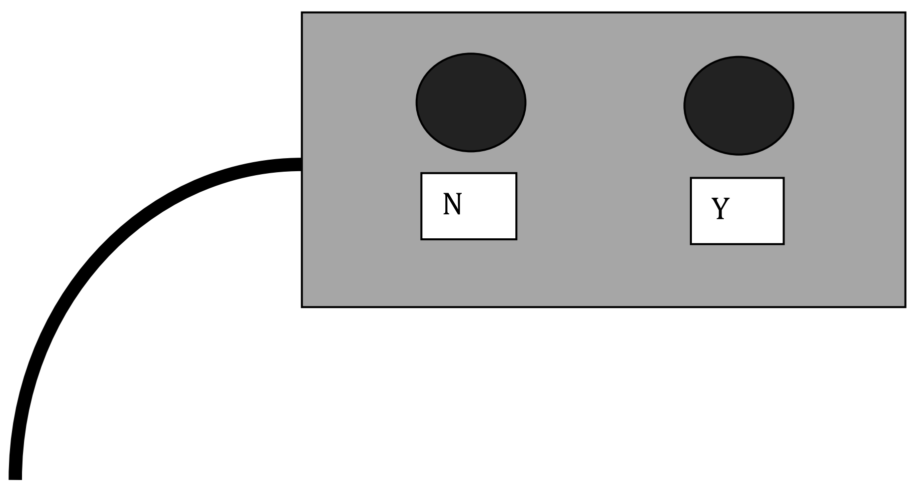
You will be seated in front of a computer display with a button box (See picture below). You will be viewing sequences of five objects. To begin please push either button. You will appear to be flying over a series of objects. Some of these sequences will follow an underlying structure and some will not. Your job is to determine if the sequences follow the underlying structure or appear to be random. If the sequence appears to have the same underlying structure, then please press the button on the button box marked “Y” for Yes. If the sequence does not follow the same underlying structure, then please press the button on the button box marked “N” for NO. You will continue to do this until you receive a message that all trials are complete.



Decision Making Study Instructions: (Training Exp. 3, Labeling Groups)

PLEASE TURN OFF YOUR CELL PHONE AND PUT IT AWAY! THE FOLLOWING TASK REQUIRES A HIGH LEVEL OF CONCENTRATION. A RINGING CELL PHONE WILL DISQUALIFY YOU FROM THE STUDY.

You will be seated in front of a computer display. You will be asked to view a series of objects on the screen. Please watch them and the experimenter may discuss what you have just viewed. While you are watching the series of objects you will be asked to verbally label the objects as you are flown over them according to the object labeling sheet. The experiment should take approximately 45-60 minutes with scheduled breaks. If you need additional breaks, please let me experimenter know. Once the experimenter tells you to begin, please push either button (as shown in the figure below).You will appear to be flying over a series of objects. These sequences will consist of five different objects in various orders on a desert-type terrain. Please watch them until you receive a message that all trials have been completed.

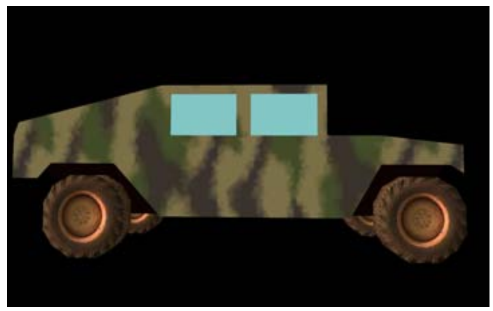


Experiment 3. Labels and Objects

Truck

Abrams

Launcher



Hummer

Bradley

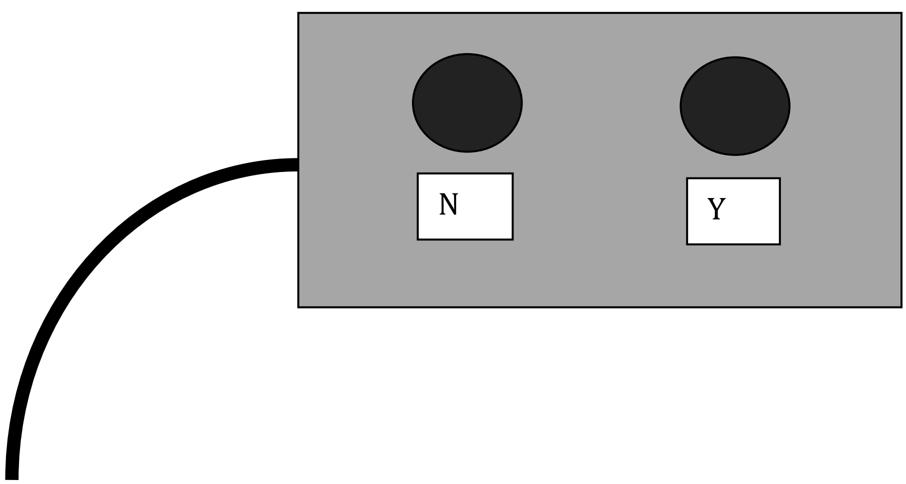
Decision Making Study Instructions: (Exp. 3, Secondary task Groups)

PLEASE TURN OFF YOUR CELL PHONE AND PUT IT AWAY! THE FOLLOWING TASK REQUIRES A HIGH LEVEL OF CONCENTRATION. A RINGING CELL PHONE WILL DISQUALIFY YOU FROM THE STUDY.

Part Two

For this portion of the experiment you will again be seated in front of a computer display with a button box (See picture below). The series of objects that you just watched form a sequence which follows a specific underlying structure. For this portion of the experiment, you will be viewing the same objects you have just viewed but in sequences you have not seen before. Some of these sequences will follow the same underlying structure you saw in the previous task and some will not. Your job is to determine if the sequences follow the same underlying structure or not. If the sequence appears to have the same underlying structure, then please press the button on the button box marked “Y” for Yes. If the sequence does not follow the same underlying structure, then please press the button on the button box marked “N” for NO. You will continue to do this until you receive a message that all trials are complete.

You have been selected to complete another activity while performing the decision. Specific activities will be described to you before beginning this portion of the experiment. Specifically, you may be instructed to tap your toes or told to repeat a syllable like “da-da”.



APPENDIX B

SIMPLE FINITE STATE ALGORITHM TRAINING AND TEST SEQUENCES

Simple Algorithm (Reber, 1967; Patterson, et al. 2009) and example Quasi-random sequences by length

Simple Algorithm	Quasi-Random Sequences
EDEC	ACDC
EEBC	EBCC
ABAC	ABCC
AADEC	ACDC
EDDEC	ECDCC
ABBAC	ACDCC
EDEBC	EBCBC
ABADEC	AABCDC
AADDEC	EBCDEC
AADEBC	ABCDEC
EDDEBC	EDEABC
EEBDEC	ACDEAC
ABBBAC	ECDEAC
EDDDEC	AABCDC
EDDDDEC	AABCDEC
ABADEBC	EBCDEAC
ABBBBAC	ADEABCC
EDEBDEC	EEABCDC
EEBDEBC	ADEABCC
ABADDEC	EABCDEC
EEBDDEC	AABCDEC
AADDEBC	EABCDEC
AADDDEC	ADEABCC
ABBADEC	ECDEABC
EDDDEBC	ABCDEAC
AADEBDEC	EABCDEAC
EDDEBDEC	ADEABCDC
ABBBBBAC	EBCDEABC
ABBADEBC	AABCDEAC
EDEBDDEC	ECDEABCC
EEBDDEBC	AABCDEAC
EEBDDDEC	EDEABCDC
AADDDEBC	AEABCDEC
ABADDDEC	EBCDEABC
AADDDDEC	AEABCDEC
EDEBDEBC	EBCDEABC
Simple Algorithm	Quasi-Random Sequences

ABBADDEC	ADEABCDC
EDDDDEBC	EBCDEABC
ABADDEBC	ADEABCDC
EDDDDDEC	EEABCDEC
ABBBADEC	AEABCDEC

APPENDIX C

COMPLEX FINITE STATE ALGORITHM TRAINING AND TEST SEQUENCES

Complex Algorithm (Reber & Allen, 1978) and example Quasi-random sequences by length

Complex Algorithm	Quasi-Random Sequences
ACDE	AACA
ABCB	ACBD
CEBC	ADBA
CECB	CCAA
CEDA	ADED
ABBC	AAEE
CEDD	CBAB
ABBCB	CDBEC
CECDE	AECBE
CEDDD	CBCEB
ACDEC	ABCBD
ABCDE	ACBDA
ABBBC	AECAE
CEBCB	AEABD
ACDEA	CDACA
CEDDA	AEDDB
ACDED	ABECB
CEBBC	ACCDA
ABCDEC	AEDDBC
ACDEDA	ADCADC
ABBBCB	ADAAEC
ACDEBC	AEBABE
CECDEA	CEEBED
CEBBCB	CDABBE
CECDED	ABCAEE
ABBBBC	CABDEC
ABCDED	ADABEE
ACDECB	ACABDE
CECDEC	AAEAEA
ABBCDE	AECACE
CEBCDE	CAACBA
ACDEDD	AECAAA
ABCDEA	CEBDEC
CEBBBC	CDBDCA
CEDDDA	CAEAAC
CEDDDD	ABABAC

Complex Algorithm	Quasi-Random Sequences
ABBCDEA	ADABBCB
CECDEBC	CABDBEA
ABCDECB	AEBCEAC
ABCDEDD	CBADDAB
CEBCDED	CDBEBAC
CEBBBBC	CCDEEEE
ACDEBBC	CDABBCA
ABCDEBC	CDCDEBE
CECDEDA	AACDDEB
ABBBBCB	CBACABC
CECDEDD	ADEDADA
ABBBBBC	CEEBDDC
ABBBCDE	CEBDEDA
CECDECB	CCCCEED
ACDEBCB	AEEADDD
ABCDEDA	CBCCCCE
CEBBCDE	CBAEBEC
ACDEDDA	CBABCCC
CEBBBCB	CBBDAAB
CEDDDDA	ADBADBD
ACDEDDD	ABDBAEA
ABBCDED	ABECAAE
ABBCDEC	CCEACAC
CEBCDEC	AEBBAAD
ACDECDE	CEBCDDE
CEDDDDD	CCEEABD
CEBCDEDD	CADDBABE
CECDEDDA	CCAADDCA
CEBBBBBC	ADACABBE
ABCDEBBC	ABBEBAAD
ABBCDEDA	ACCCDCBD
ACDEBBBC	AADEEAEE
ABBBBCDE	ABDBDECB
CEBBCDEA	AADDCEBC
CEBCDECB	AEEADDEA
ACDEDDDA	CAEDCACA
CEBBCDED	CEBDBEAE
ABCDEDDA	CDADDEEC
ABBCDEDD	ABEDDEAA

Complex Algorithm	Quasi-Random Sequences
ACDEDDDD	CEADADDD
ABCDEBCB	CDBBDCAD
CECDECDE	AEBCBAAA
ABBBCDEC	ADBDAABD
ABBBBBCB	CBDAADEE
ABBCDECB	AECCADBC
ABBBCDEA	CAEECAEE
ABCDEDDD	ABADCCAA
ABBBBBBC	AADDCDDB
ABCDECDE	ABBCBCAA
ACDECDEC	CAAEAADE
CEDDDDDA	ABCDDBCA
CEDDDDDD	CACADECD
ACDEBCDE	CDADCEDE
ACDECDED	CAEECCDE
CEBBBBCB	AECBCBEB
CEBCDEDA	CDDEDBBD
CECDEBBC	CAAEBBDD
CECDEBCB	CCBDBDDE
ABBCDEBC	AEBBADDD
CECDEDDD	CCEAEABD
CEBCDEBC	ABADDBDE
ABBBCDED	AABDEADE
ACDECDEA	ADEAECCC
CEBBBCDE	ACBCADAE
ACDEBBCB	AACBBEAC
CEBBCDEC	CBDBDACC

APPENDIX D

INSTITUTIONAL REVIEW BOARD DOCUMENTS:

ARIZONA STATE UNIVERSITY

INFORMATION LETTER
Immersive Environments Study 03/22/2010

Dear ASU Research Participant:

I am a graduate student under the direction of Professor Nancy Cooke in the College of Technology and Innovation, Applied Psychology Program at Arizona State University. I am conducting a research study to investigate learning within immersive environments.

I am inviting your participation, which investigate how individuals learn within simulated three-dimensional environments (virtual worlds generated by a computer and depicted on a large display). The time requirement for each participant is anticipated to be 1 visit of approximately 0.5 hour to 1.5 hours. To participate, you must have normal or corrected to normal vision. At the beginning of the study, a number of eye tests similar to tests given to obtain a drivers license (acuity, binocular vision, color vision, and phoria) will be administered. You may be excluded from the study if your vision does not test as normal/corrected to normal. You will then be asked to watch set of episodes in which you will be flown within a virtual world composed of simulated natural terrain and objects. You have the right not to complete any aspect of this investigation, and to stop participation at any time.

Your participation in this study is voluntary. If you choose not to participate or to withdraw from the study at any time, there will be no penalty. You must be 18 or older to participate in the study. If you are a participant from the ASU Psychology Subject pool you will be given 1 hour of credit for participation. If you are a volunteer who is not from the subject pool you will be paid ten dollars for participation.

The benefits to you from participating in this study will be the educational experience of participation in a formal research project. Minimal risks are involved in participation which includes: possible fatigue, eye strain, nausea, and/or headache as a result of viewing the display system in this experiment. The frequency of occurrence is no more likely than that which you might experience when working at a computer workstation or watching television. Preventative measures include proper posture while sitting, frequent breaks, and wearing proper corrective lenses if applicable. If at any time you feel uncomfortable please let the experimenter know and he/she will stop the experiment.

All information obtained in this study is confidential. The results of this research study may be used in reports, presentations, and publications, but researchers will not identify you. Your data will be coded in such a way that there will be no way to link the data files with your identity. It is intended that the only people having access to your information will be the researchers named below. When no longer needed for research purposes your information will be destroyed in a secure manner (shredding/deleting).

Any questions you have concerning the research study or your participation in the study, before or after your consent, will be answered by Christine Covas-Smith, ccovas@asu.edu, (602)315-3608 or Nancy Cooke, Nancy.Cooke@asu.edu, (480)988-2173. If you have any questions about your rights as a subject/participant in this research, or if you feel you have been placed at risk, you can contact the Chair of the Human Subjects Institutional Review Board, through the ASU Office of Research Integrity and Assurance, at (480) 965-6788. Please let me know if you wish to be part of the study.

ASU ARIZONA STATE UNIVERSITY
RESEARCH AND ECONOMIC AFFAIRS

Office of Research Integrity and Assurance

To:	Nancy Cooke Dept. of A
From:	Mark Roosa, Chair Soc Beh IRB
Date:	03/05/2010
Committee Action:	**Exemption Granted**
IRB Action Date:	03/05/2010
IRB Protocol #:	1003004888
Study Title:	Implicit Learning in Immersive Environments

The above-referenced protocol is considered exempt after review by the Institutional Review Board pursuant to Federal regulations, 45 CFR Part 46.101(b)(2).

This part of the federal regulations requires that the information be recorded by investigators in such a manner that subjects cannot be identified, directly or through identifiers linked to the subjects. It is necessary that the information obtained not be such that if disclosed outside the research, it could reasonably place the subjects at risk of criminal or civil liability, or be damaging to the subjects' financial standing, employability, or reputation.

You should retain a copy of this letter for your records.

APPENDIX E

INFORMED CONSENT DOCUMENTS:

AIR FORCE RESEARCH LABORATORY

INFORMATION PROTECTED BY THE PRIVACY ACT OF 1974

Informed Consent Document
For
Entity Modeling and Simulated real-world Decision Environments

AFRL/RHAE, Mesa Research Site, Mesa, AZ

Principal Investigator: Dr. Byron Pierce, Simulated real-world Environments Principal Scientist, DSN 474-6219, AFRL/RHAE, Byron.pierce@mesa.afmc.af.mil

Associate Investigators: Ms. Christine Covas-Smith, Associate Research Psychologist, DSN 474-6547, Cell 602-315-3608, AFRL/RHAE, ASU, Christine.Covas@mesa.afmc.af.mil, ccovas@aol.com

Dr. Robert Patterson, Senior Research Psychologist, (509) 432-3078, Robert.patterson@mesa.afmc.af.mil

1. **Nature and purpose:** You have been offered the opportunity to participate in the "Simulated real-world Decision Environments Research: Replication" study. Your participation will occur at the Mesa Research Site Simulated real-world Decision Environments Research Laboratories or at the Arizona State University Campus. The purpose of this research is to evaluate Human Factors performance in flight simulation and training applications.

The time requirement for each volunteer participant is anticipated to be a total of 2 to 12 visits of approximately 0.5 hour to 2 hours each. A total of approximately 600 participants may be enrolled in this experiment and related research experiments. In order to participate you must have normal or corrected to normal vision. At the beginning of the study, a number of eye tests will be administered. You may be excluded from the study if your vision does not test as normal (or corrected to normal), however if you are a paid volunteer, you will be compensated for your time during the testing procedure. If you are an AFRL/RHA SME or Air Force pilot on TDY who has volunteered to participate in this research, you will have to arrange for the time to participate through your supervisor or host. If you are an ASU Psychology pool participant you will be compensated in credit hours through the subject pool list.

2. **Experimental procedures:** If you decide to participate, you will be asked to view a visual display and detect or identify a simulated air or ground model, read or identify text and symbology, track a moving object, or control heading or altitude of a simulated aircraft. You may be asked to perform two or more of these tasks simultaneously. While performing these tasks your reaction time, accuracy, tracking error, or direction of gaze may be recorded. To record your responses you will be asked to provide input via a mouse, joystick, keyboard, or flight control deck. Prior to performing the task, or immediately following the task, the

experimenter may also ask you a series of questions. The questions will relate only to the quality of the visual display or whether or not you experience any headache, eyestrain, nausea, or other physiological discomfort after viewing the visual display. No other questions or personnel data will be requested of you. Prior to beginning the experiment, the experimenter will provide you with a document detailing your task for this experiment (i.e. which buttons to press on the input device, etc.). The experimenter will also verbally describe the task, and you will be given an opportunity for practice. If you have any questions at all regarding the procedure please feel free ask the experimenter at any time.

You will be seated in a chair in an air conditioned room and the lights may be dimmed. Your participation may be a maximum of two hours per day for no more than two weeks. Opportunities for rest breaks will be given at the end of each set of trials. Should you require additional rest breaks at any time, please inform the experimenter and he or she will pause the experiment. Restrooms, water, and vending machines are available. Should you feel uncomfortable at any time or wish to discontinue the experiment for any reason, please inform the experimenter and he or she will end the experiment.

3. **Discomfort and risks:** There are minimal risks involved in participating in this experiment. These risks are possible fatigue, eye strain, nausea, and/or headache as a result of viewing the display systems in this experiment. The frequency of occurrence of such risks is no more likely than that which you might experience when working at a computer workstation or watching a television or movie. Preventative measures you may take include proper posture while sitting/standing, frequent breaks, and wearing proper corrective lenses if applicable. If at any time you feel uncomfortable please let the experimenter know and he/she will stop the experiment.

4. **Precautions for female subjects, or subjects who are or may become pregnant during the course of this study:** There are no known additional precautions required for female participants.

5. **Benefits:** The benefits to you from participating in this study will be the potential discovery of visual dysfunction, such as poor visual acuity or lack of binocularity, during the initial screening procedures, and the educational experience of participation in a formal research project.

6. **Compensation:** If you are a paid volunteer your compensation for volunteering to participate in this research experiment will be $10 per hour. At the end of the week you will receive a voucher with your pay information. You will be required to take this voucher to the Cognitive Research Institute (CERI) on Fridays between the hours of 11:00am and 4:00pm for payment. Their address is 5810 South Sossaman Rd. Ste. 106 Mesa, AZ 85212 -5826 and their phone number is 480-988-9306. ASU Psychology Participants will be compensated by the ASU subject pool office using credit hours. Note that participants who are active duty, RHA contract support and RHA government employees will not be compensated for participation.

7. **Alternatives:** Participation in this experiment is entirely voluntary. Choosing not to participate is your alternative to participating. There are no penalties for withdrawing for any reason. Should you choose to discontinue participation, and if you are a paid volunteer, you will be compensated for the time that you did participate.

8. **Entitlements and confidentiality:**

a. Records of your participation in this study may only be disclosed according to federal law, including the Federal Privacy Act, 5 U.S.C. 552a, and its implementing regulations. Your personal information will be stored in a locked cabinet in an office that is locked when not occupied. Electronic files containing your personal information will be password protected and stored only on a DoD server. It is intended that the only people having access to your information will be the researchers named above and the AFRL Wright Site IRB or any other IRB involved in the review and approval of this protocol. When no longer needed for research purposes your information will be destroyed in a secure manner (shredding). Complete confidentiality for military personnel cannot be promised because information bearing on your health may be required to be reported to appropriate medical or command authorities.

Your entitlements to medical and dental care and/or compensation in the event of injury are governed by federal laws and regulations, and that if you desire further information you may contact the base legal office (88 ABW/JA, 257-6142 for Wright-Patterson AFB). In the event of a research related injury, you may contact the medical monitor, Sarah Fortuna/MAJ/IRB Chair and/or Medical Monitor 711 HPW/IR 4-8100 sarah.fortuna@wpafb.af.mil .

b. If an unanticipated event (medical misadventure) occurs during your participation in this study, you will be informed. If you are not competent at the time to understand the nature of the event, such information will be brought to the attention of your next of kin or other listed emergency contact.

Next of kin or emergency contact information:

Name_______________________ Phone#_________________

c. The decision to participate in this research is completely voluntary on your part. No one may coerce or intimidate you into participating in this program. You are participating because you want to. Dr. Byron Pierce, or an associate, has adequately answered any and all questions you have about this study, your participation, and the procedures involved. Dr. Byron Pierce can be reached at (480) 988-9773 x219. Dr. Byron Pierce or an associate will be available to answer any questions concerning procedures throughout this study. If significant new findings develop during the course of this research, which may relate to your decision to continue participation, you will be informed. You may withdraw this consent at any time and discontinue further participation in this study without prejudice to your entitlements. The investigator or medical monitor of this study may terminate your participation in this study if she or he feels this to be in your best interest. If you have any questions or concerns about your participation in this study or your rights as a research subject, please contact Dr. Byron Pierce, Simulated real-world Environments Principal Scientist at (480) 988-9773 x219, Byron.Pierce@mesa.afmc.af.mil or Sarah Fortuna/MAJ/IRB Chair and/or Medical Monitor 711 HPW/IR 4-8100 sarah.fortuna@wpafb.af.mil .

d. Limited personal information will be collected. This may include your name, age, gender, and visual screening results. This information will be kept in a password protected electronic database and will remain there for approximately five (5) years. No personal information will be stored on removable storage devices, laptops, or personal computers. Data collected from you will not be stored with identifying information but will be coded by the experimenter. This data will also be stored in a password protected electronic database and will remain there indefinitely.

e. Your participation in this study may be photographed, filmed or audio/videotaped. You consent to the use of these media for training and data collection purposes. Any release of records of your participation in this study may only be disclosed according to federal law, including the Federal Privacy Act, 55 U.S.C. 552a, and its implementing regulations. This means personal information will not be released to unauthorized source without your permission. These recording may be used for presentation or publication. They will be stored in a locked cabinet in a room that is locked when not occupied. Only the investigators of this study will have access to these media. They will be maintained for 5 years.

YOU ARE MAKING A DECISION WHETHER OR NOT TO PARTICIPATE. YOUR SIGNATURE INDICATES THAT YOU HAVE DECIDED TO PARTICIPATE HAVING READ THE INFORMATION PROVIDED ABOVE.

Volunteer Signature____Date____________

Volunteer Name (printed)____

Advising Investigator Signature _______________________ Date ____________

Investigator Name (printed)____

Witness Signature ____________________________________Date ____________

Witness Name (printed)____

Privacy Act Statement

Authority: We are requesting disclosure of personal information, possibly to include your Social Security Number. Researchers are authorized to collect personal information (including social security numbers) on research subjects under The Privacy Act-5 USC 552a, 10 USC 55, 10 USC 8013, 32 CFR 219, 45 CFR Part 46, and EO 9397, November 1943.
Purpose: It is possible that latent risks or injuries inherent in this experiment will not be discovered until sometime in the future. The purpose of collecting this information is to aid researchers in locating you at a future date if further disclosures are appropriate.
Routine Uses: Information (including name and SSN) may be furnished to Federal, State and local agencies for any uses published by the Air Force in the Federal Register, 52 FR 16431, to include, furtherance of the research involved with this study and to provide medical care.
Disclosure: Disclosure of the requested information is voluntary. No adverse action whatsoever will be taken against you, and no privilege will be denied you based on the fact you do not disclose this information. However, your participation in this study may be impacted by a refusal to provide this information.