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Does Observational Learning Influence Spatial Pattern Learning?

Matthew Bruster

DOES OBSERVATIONAL LEARNING INFLUENCE SPATIAL PATTERN LEARNING?

by

MATTHEW BRUSTER

(Under the Direction of Bradley Sturz)

ABSTRACT

Previous studies have indicated both human and non-human animals come under control of a hidden spatial pattern when engaged in an open field search task, and rats appear to exhibit social learning in such tasks through the influence of a conspecific on their search behavior. Although human participants appear to perform similarly in both real-world and virtual environment versions of a spatial pattern search task, evidence from human participants for social learning in such a task remains lacking. The current experiments tested the influence of social learning (observational learning) on human performance in a spatial pattern learning task within a virtual environment. In Experiment 1, participants watched a video of a demonstrator performing a spatial pattern learning task using either a random search strategy (Random Observation Group) or an optimal search strategy (Optimal Observation Group). Participants then completed 30 trials of the search task by locating four goals arranged in a diamond pattern. The search task required participants to search within a 5 x 5 matrix of bins in a virtual environment for the four goal locations. Results suggested participants in the Optimal Observation Group performed superior to participants in the Random Observation Group on all behavioral measures of search performance. Experiment 2 tested if the obtained differences in Experiment 1 resulted from facilitation of learning in the Optimal Observation Group or inhibition of learning in the Random Observation Group by adding a third Control No Observation group. Results of Experiment 2 suggested that participants in the Optimal Observation Group performed superior to participants in the Random Observation and Control No Observation groups. No differences emerged between the Random Observation and the Control No Observation groups. Collectively, results provide evidence for social (observational) learning by humans in a spatial pattern learning task and suggest facilitation of learning in the optimal observation group drove group differences in performance.

INDEX WORDS: Spatial pattern learning, Social learning, Observational learning, Virtual environment

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MATTHEW BRUSTER

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MATTHEW BRUSTER

Major Professor: Bradley R. Sturz
Committee: Kent D. Bodily
Lawrence Locker, Jr.

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CHAPTER 1:

INTRODUCTION

Learning can be described as a change in an organism's behavior based on past experiences (Chance, 2009). The ability to change behavior based upon experience is evolutionarily beneficial. For example, chances of survival are increased if an organism can learn to avoid locations more likely to contain a threat or learn to efficiently navigate between food sources. Historically, the learning process has been studied via direct personal experience (i.e., associations between stimuli). The originator of this line of inquiry was Ivan Pavlov and his work with classical conditioning (Pavlov, 1927). Through Pavlov's work with animals, the mechanisms of stimulus-stimulus learning were discovered. The behavior of early study focused on physiological responses elicited by stimuli which allowed learning to be viewed mechanistically utilizing inputs and outputs. The rate of learning was measured by how many exposures of a stimulus were required to elicit the desired response. An animal was said to be conditioned when an unconditioned stimulus (a stimulus that naturally elicits a response) was paired with a neutral stimulus (a stimulus which elicited no response). After successive pairings, the neutral stimulus came to elicit the same response from the organism as the unconditioned stimulus.

While this method of learning is accurate, it appears to minimize the active role an organism plays in the environment. The complex interaction between environment and organism was explored by B. F. Skinner and his work detailing operant conditioning (Skinner, 1974). Skinner's (1974) principles of operant conditioning allowed researchers to better understand the complex interactions between organisms and their environment through the consequences of behavior (i.e., punishing or reinforcing qualities of each interaction with the environment). Skinner studied operant conditioning with rats in operant chambers, colloquially known as "Skinner boxes," where a rat's behavior was reinforced with food when it pressed a level found in the chamber (Skinner, 1938). Within these paradigms, Skinner built the foundation for understanding the ability of an organism to engage in complex behaviors through the use of shaping behavior (reinforcement of successive approximations of a target behavior) and chaining behavior (reinforcement of independent behaviors within a series to form one complex behavior) that result in an organism engaging in more complicated behaviors to receive a reinforcer. The simple principles of reinforcement and punishment found in operant conditioning allowed researchers to study and understand the environmental factors that influence an animal’s behavior. Researchers have been able to determine multiple environmental factors can influence the behavior of an animal, including, but not limited to, olfactory stimuli (April, Bruce, & Galizio, 2011) and auditory stimuli (Reed & Yoshino, 2008). For example, pigeons switch from pecking one disk to another based upon changes in a stimulus, indicating environmental changes result in changes to the behavior of the animal (McMillian & Roberts, 2012).

Additional paradigms such as shaping and reinforcing techniques have been developed to study behaviors in specific domains. Radial arm mazes, which are apparatuses consisting of a central platform with multiple arms radiating out from the platform with a reinforcer located at the end of the arm and out of view from the central platform, have been used to suggest that animals are able to recall previous locations of a reinforcer and learn to avoid visiting these locations when the reinforcer has been depleted (Olton & Samuelson, 1976). Similarly, rats appear to be able to utilize spatial information derived from intramaze (landmarks or characteristics inside the maze) and extramaze (landmarks or characteristics outside of the maze but within the experimental room, i.e., a clock or poster on the wall of the experimental room) cues to determine the location of a reinforcer (Brown, Rish, VonCulin, & Edberg, 1993).

Within the realm of spatial learning, Brown and colleagues (1996, 2000, 2001) investigated the extent to which rats can learn the spatial arrangement of hidden goal locations within a series of studies and utilized food to investigate the ability of previously unknown and hidden goal locations to control the behavior of rats. In one study, Brown and Terrinoni (1996) utilized a 5 x 5 matrix of poles that were baited with food pellets in a hole drilled into the top of each pole. The researchers baited the poles utilizing the same spatial relationship between each goal location across each trial but varied where the goal locations were located within the matrix. Multiple measures of search behavior (e.g., number of errors to locate all four goal locations, direction of movement after discovery of a goal location, number of errors to locate successive goal locations) indicated spatial pattern learning. The patterns that were found to control the search behavior were a 2 x 2 square and a line that was formed by baiting a single row or column. The researchers suggested the rats were able to come under control of the patterns, and subsequent follow up experiments have indicated this control also applies to other spatial patterns, such as a checker board pattern (Brown, Zeiler, & John, 2001**).**

Brown, Digello, Milewski, Wilson, and Kozak (2000) utilized a similar apparatus to investigate rats' ability to come under control of both a pattern and another cue **-** the conditional cue being food type. The researchers utilized the same spatial patterns from the study discussed above, which were a baited 2 x 2 square and a line formed by baiting a single row or column. However, in this study, the researchers used a 4 x 4 matrix of poles instead of a 5 x 5 matrix of poles. The researchers utilized either sunflower seeds or sucrose pellets to form a 2 x 2 square and either sucrose pellets or sunflower seeds to form a line pattern, keeping the food consistent for each spatial pattern for individual subjects. Researchers also balanced the number of subjects who received the sucrose pellet line with the number of subjects receiving the sunflower seed line and the same with the 2 x 2 square. The rats were found to come under control of the spatial pattern formed by the goal locations, as well as their search behavior being influenced by the type of food found in the trial. That is, when the line formed by a baited column or row was baited with sucrose pellets, rats searched in adjacent poles conforming to the line pattern after discovery of the second sucrose baited pole. In contrast, when sunflower seeds were used to bait the 2 x 2 square, rats would engage in search behavior conforming to the square pattern after discovery of the second sunflower seed baited pole. Analysis of choices by the rats immediately after discovery of the second and third baited poles revealed search behavior of the rat changed based on food source. In both experiments, proportions of moves that conformed to the patterns were greater than expected by chance, showing control by both food type and pattern. These results are indicative of the flexible nature of spatial pattern learning and can allow for animals to come under control of multiple complex patterns based on environmental factors.

Using a pole box maze, Brown, Zeiler, and John (2001) created a checkerboard pattern by alternating goal and non-goal locations over the entirety of the 4 x 4 pole box maze (Experiment 1) and the 5 x 5 pole box maze (Experiment 2). Researchers used this pattern because the spatial relationships can be extrapolated indefinitely, meaning the alternating pattern of goal and non-goal location can be repeated non-stop given the space. In Experiment 1, the researchers found evidence that rats came under control of the checkerboard pattern. Rats were more likely to engage in skip movements (bypassing the next pole on the same row or column to reach a pole separated by the bypassed pole) and diagonal movements (choosing a pole located diagonally to the pole) after choosing a baited pole, which made the rat more likely to find a reinforcer in the next chosen pole.

Recently, Sturz, Kelly, and Brown (2009) have shown similar results with human participants. Specifically, Sturz et al. (2009) utilized a similar protocol within both real and virtual environments to investigate cue competition (when multiple stimuli compete to become predictors of following events, e.g., blocking, overshadowing) in a search task. The real environment was a search space covered in shredded paper with a 5 x 5 matrix of raised bins contained within the search chamber. The raised bins were also filled with shredded paper. The participants searched within the environment for four red plastic balls underneath the shredded paper in the raised bins with the red balls arranged in a 2 x 2 pattern. Participants were assigned to either a cue + pattern group or a pattern only group, the difference being the cue + pattern group searched in an environment with four black raised bins arranged in the square pattern and housed the goal location during training, whereas in the pattern only group, all raised bins were the same red color. The virtual environment followed the same training protocol with a 5 x 5 matrix of raised bins containing either 25 identical tan bins or 21 tan bins and four red bins in the square pattern, indicating the goal location and the spatial pattern of the goals. During the testing phase of the experiment, all of the pots and bins were identical. Sturz et al. (2009) examined the number of errors to complete a trial (locating all four goal locations) during the training phase and determined the presence of cues facilitated the learning of the spatial pattern, indicated by participants in the cues + pattern groups in both real and virtual environments making fewer errors completing the trials than the pattern only group.

To analyze the testing phase, Sturz et al. (2009) examined the number of errors after discovery of the third goal location to determine if participants search behavior adhered to the square pattern. Results indicated all participants made fewer errors after discovery of the third goal location than expected by chance, with participants in the cues + pattern group making fewer than the participants in the pattern only groups. This again is indicative of cues facilitating learning of the spatial pattern instead of competing with the spatial pattern. Researchers also determined that participants across real and virtual environments performed similar to each other, indicating the virtual environment can be utilized to gather data reflective of real-world performance.

Sturz, Kelly, and Brown (2010) utilized the same real and virtual environment as described in the previous study to examine the influence of landmarks, cues, and spatial patterns with learning the goal locations. The real environment utilized raised bins with the landmark and cue groups with green bins to act as either the landmark or cue. The virtual environment utilized the same colors as the previous study with tan and red raised bins and followed the same protocol as the real environments. Participants were searching for four goal locations arranged in a diamond shape around one non-goal location. Participants were assigned to one of three groups: pattern only, landmark + pattern, or cues + pattern. While in the testing phase, participants in the pattern only group were only trained with the hidden spatial pattern, participants in the landmark + pattern group were trained with the non-goal location at the center of the diamond pattern marked in green, and participants in the cues + pattern group were trained with the goal locations marked in green. The training was the same for both real and virtual environments. Search behavior from both training and testing phases were examined by mean number of errors to locate all four goal locations, and search behavior from the testing phase was examined by the proportion of diagonal moves after discovery of a goal location. Results indicated that all groups came under control of the spatial pattern with both cues + pattern and landmark + pattern preforming superior to the pattern only group on all measures. Researchers found, in the training phase, participants were not hampered by the presence of either a landmark or cues and, in fact, both landmarks and cues facilitated learning the spatial pattern more quickly than the pattern only group. Further, the landmark + pattern and the cues + pattern groups preformed identically during the testing phase. Again, performance of participants in real and virtual environments did not differ. Results of this experiment again suggest that cue competition did not occur between features and the diamond pattern and the presence of a cue, such as a land mark, facilitated the learning of the diamond pattern.

The studies discussed above rely on the personal experience of an animal to measure learning, but learning does not require the organism to rely on personal experiences. For example, some animals have exhibited the ability to learn though observations of others (including conspecifics). Such learning has been termed “observational learning” (for a review, see Zentall, 2012). Collectively, these types of learning are referred to as “social learning” because they require social interactions with other animals. Evidence for social learning has been observed in multiple species including: primates (Fragaszy & Visalverchi, 1996), rats (Brown, Saxon, Bisbings, Evans, Ruff, & Stokesbury, 2015; Keller & Brown, 2011; Terkel, 1996), and humans (Huang, 2012; Iani, Rubichi, Ferraro, Nicoletti, & Gallese, 2013). For example, Fragaszy, Geuerstein, and Mitra (1996) provided evidence that the phenomenon of social facilitation occurs in primates. Social facilitation is an increase in frequency of a behavior when in the presence of conspecifics engaged in the same behavior. The researchers exposed young capuchin monkeys to shelled nuts either individually or in a social condition, which meant that the young capuchins were exposed to the shelled nuts in the presence of an older capuchin more familiar with cracking the shell and obtaining the nut within. The researchers observed that the young capuchins appeared to learn similar techniques to the older capuchin to open the nut, although this was done in a non-direct manner without the older capuchin formally teaching the young capuchin. This finding coupled with the young capuchins greater interest in the nuts held by older capuchins led researchers to conclude that the social environment and social interactions are both influential to learning.

Social interactions and the social environment have also been theorized to influence the behavior of humans. Bandura (1971) proposed in his social learning theory that attentional processes, retentional processes, motor reproductive processes, and motivational processes influenced whether or not the observer would learn from the demonstrator. The attentional processes include whether or not the observer is observing the relevant parts of the demonstrator's behavior. If the observer attends to the demonstrator's behavior, then the observer also must retain information gathered from watching the behavior of the demonstrator and possess the physical ability to properly reproduce the behavior. Determining whether or not an observed behavior will be imitated is dictated by the expectation of reinforcement after engaging in the observed behavior (Bandura, 1971). However, there are also characteristics of the demonstrator (e.g., as being a conspecific, consequences of the demonstrator experiences) that influence social learning. If the behavior of the demonstrator fails to provide reinforcement for the demonstrator, the behavior is less likely to be imitated by an observer. If the informative function of the demonstrator's behavior is determined to be important and lead to reinforcement, then the likelihood of the demonstrator's actions being imitated by the observer are increased (Bandura, 1971).

Within the realm of spatial learning, Brown and colleagues (1996, 2000. 2001) have provided evidence that rats' spatial behaviors within an environment are socially influenced by interactions and observations with other rats. For example, Brown, Farley, and Lorek (2007) utilized a radial arm maze to investigate the effects of observational learning on the behavior of rats. The radial arm maze consisted of eight arms radiating out from a center platform that allowed access to each of the eight arms Within the center platform was an observation cage that allowed an observer rat to witness the choices made by a demonstrator rat prior to taking part in trails within the radial arm maze. Using both forced-choice tests (blocking access to four arms of the maze) and free-choice tests (having access to all eight arms of the maze) researchers sought to determine if choices made by one rat were influenced by choices made by its cage mate. Researchers found that rats had a tendency to visit the most recent arm choice of their cage mate, most likely facilitated by the presence of the cage mate, but also had a tendency to avoid previous arms that the cage mate visited one or more choices earlier.

Keller and Brown (2001) provided evidence that social interactions influence the choices made by rats in an open field pit maze. In this experiment, the researchers exposed rats to a pit maze in either pairs or individually after an acclimating and training period. Each animal participated in both individual and paired trials. The pit maze task required the animals to navigate a 5 x 5 matrix of covered pits in the floor of the square enclosure in search of hidden sucrose pellets found in the bottom of the pit. The authors found that rats in the social condition showed a tendency to avoid pits previously visited by the other rat throughout the experimental period. This led the researchers to the conclusion that social interactions and memories for the other rats' behavior influenced the behavior of the focal rat (Keller & Brown, 2011).

Purpose of the Study

Although rats and humans appear able to learn the spatial relationship between hidden goal locations, and social learning appears to affect rat's performance on spatial pattern learning tasks, it remains an open question as to whether human performance within a similar spatial task would also be affected by social learning. The purpose of the present experiments was to examine the influence of social learning on humans' performance on a spatial pattern learning task in a virtual environment. In Experiment 1, participants watched a demonstrator complete a spatial pattern learning task utilizing either an optimal search strategy or a random search strategy. To the extent that observational learning influences human spatial performance, participants who watched the demonstrator use an optimal search strategy should demonstrate superior performance on multiple behavioral measures of search behavior in the spatial pattern learning task compared to those who watched the demonstrator use a random search strategy.

CHAPTER 2:

EXPERIMENT 1 METHODOLOGY

Participants

Participants in this study were 48 (24 female, 24 male) undergraduate students at Georgia Southern University. Participants were recruited using an online experiment management software and received extra-course credit.

Apparatus

The apparatus consisted of a Lenovo ThinkCentre computer, Lenovo ThinkVision L2250p 22-inch computer monitor, and a Logitech Gamepad F310. The virtual environment was designed and built in the Half-life^{tm} Source engine with dimensions (length x width x height) measured in virtual units (vu). The virtual environment (1,050 x 980 x 416 vu) consisted of an open room with a 5 x 5 matrix of bins (each bin was 86 x 86 x 38 vu) in the center of the room (See Figure 1).

Procedure

Participants were randomly assigned to one of two groups: Optimal Observation Group (n=24) or Random Observation Group (n=24) with gender balanced both between and within groups**.** Participants watched a video of a digital avatar completing six trials of the spatial pattern learning task using either an optimal search strategy (Optimal Observation Group) or a random search strategy (Random Observation Group). For each trial of the six trials, a diamond pattern was randomly assigned to one of nine locations (see Figure 2), and the four bins constituting the pattern were designated as goal locations. The optimal search strategy was defined as full knowledge of the spatial arrangement of goal locations (i.e., diamond pattern, see Figure 2) but not the location of the four goals within each trial (the locations of the goals moved randomly trial-to-trial), as well as utilizing information resulting from the selection of a bin (goal location or non-goal location) to minimize the number of errors to complete a trial by only making search moves consistent with the spatial arrangement of goal locations and not returning to previously visited bins. Specifically, given the diamond pattern spatial arrangement of goal locations, the optimal search strategy required four components: 1) searching the center 3 x 3 matrix first (as at least one goal location was always located within this matrix), 2) after discovery of the first goal location, searching was limited to diagonal bins from the goal location (the diamond patterns requires the next goal location to be diagonal from the previous goal location), 3) using goal or non-goal location information to limit the next diagonal searches for the second and third goal locations to the bins that are consistent with the diamond pattern, and 4) using information from all three goal locations to limit the final search to the fourth goal location. The random search pattern was defined as total lack of knowledge of the spatial arrangement of the goal locations or their location within the virtual environment, and was characterized as a pure random search. Each bin was assigned a number (1 to 25 from left to right and bottom to top from the starting location), and a random number generator was used to create a random sequence of searchers from 1 to 25 (insuring that all four goal bins would be discovered) for each of the six trials. After viewing the digital avatar complete six trials of either search strategy, the participants then completed 30 trials within the virtual environment.

During the video, participants viewed the search task from a first-person perspective and saw the demonstrator's digital avatar as a separate entity completing the search task. As the avatar maneuvered within the environment, auditory feedback indicated movement (footstep sounds). Auditory feedback of a "huh" sound indicated a jump occurred, which was required to enter into each bin. Selection of a goal bin was indicated by auditory feedback of a "ding" sound while selection of a non-goal bin was indicated by auditory feedback of a "buzzer" sound. Discovery of the first, second, and third goal locations were followed by auditory feedback indicating a goal location. After the avatar discovered all locations, auditory feedback was provided and indicated a goal location followed by a one-second intertrial-interval, in which the monitor went black and the avatar progressed to the next trial.

Following the viewing of the video, participants picked up the gamepad and began trial one of the search task in first-person perspective (identical to what was viewed when watching the avatar, but now the avatar was absent). Participants completed 30 trials of the spatial pattern learning task. For each trial, the diamond pattern was randomly assigned to one of nine locations (see Figure 2), and the four bins constituting the pattern were designated as goal locations. For each trial, participants were required to locate the four goal bins that transported them to the next trial. Participants moved via the left joystick on the gamepad: ↑ (forward), ↓ (backward), ← (rotated view left), and → (rotated view right). As with the avatar, auditory feedback indicated movement within the environment (footstep sounds). Participants selected a bin by jumping into it. To jump into a bin, participants simultaneously moved forward and jumped (gamepad button). Auditory feedback indicated a jump occurred ("huh" sound). Selection of a goal bin resulted in auditory feedback ("ding" sound). Selection of a non-goal bin resulted in a different auditory feedback ("buzzer" sound) and participants were required to jump out of the bin and continue searching. Successful discovery of the first, second, and third goal locations were followed by auditory feedback indicating a correct response. After discovery of all locations, participants received auditory feedback, indicating a correct response, which was followed by a one-second intertrial-interval in which the monitor went black and participants progressed to the next trial.

CHAPTER 3:

EXPERIMENT 1 RESULTS

To determine the extent to which observational learning occurred, four separate two-way mixed analyses of variance (ANOVAs) were conducted on the following dependent variables: mean errors to complete a trial, mean proportion of adjacent moves following the discovery of a goal location, mean proportion of diagonal moves following the discovery of a goal location, and mean proportion of first moves conforming to the optimal pattern. Analysis of these variables allowed determination of group differences and the extent to which both groups came under control of the spatial arrangement of goal locations.

Errors to Complete a Trial

A two-way mixed ANOVA on mean errors to complete a trial with Group (Optimal Observation, Random Observation) and Trial Block (1-6) as factors revealed a main effect of Group, $F(1, 46) = 16.02$, $p < .001$, a main effect of Block, $F(5, 230) = 23.66$, $p < .001$, and a significant Group x Block interaction $F(5, 230) = 5.42$, $p < .001$. As shown in Figure 3, the source of the interaction appears to result from the differences between the Groups for some trial blocks but not others. To isolate the source of the interaction six independent samples *t*-tests were conducted. Mean errors to complete a trial were significantly different between groups for all trial blocks $ts(46) > 5.2$, $ps < .05$, with the exception of Block 5, $t(46) = 1.88$, $p = .07$. These results suggest that mean errors to complete a trial decreased for both groups across trial blocks and that the Optimal Observation group made fewer errors to complete a trial across all trial blocks (with the exception of Block 5).

Proportion of Adjacent Moves following the Discovery of a Goal Location

A two-way mixed ANOVA on mean proportion of adjacent moves following the discovery of a goal location with Group (Optimal Observation, Random Observation) and Trial Block (1-6) as factors revealed a main effect of Group, $F(1, 46) = 17.99$, $p < .001$. Neither the effect of Block, $F(5, 230) = 1.31$, $p = .26$, nor the interaction $F(5, 230) = 1.24$, $p < .29$ were significant. As shown in Figure 4, the Optimal Observation Group ($M = .22$, $SEM = .08$) made fewer adjacent moves following the discovery of a goal location compared to the Random Observation Group (*M* = .67, *SEM* = .08). These results suggest that the Optimal Observation Group was making fewer moves that were inconsistent with the pattern as compared to the Random Observation Group from the beginning of the experiment and maintained this difference throughout the duration of the experiment.

Proportion of Diagonal Moves following the Discovery of a Goal Location

A two-way mixed ANOVA on mean proportion of diagonal moves following the discovery of a goal location with Group (Optimal Observation, Random Observation) and Trial Block (1-6) as factors revealed only a main effect of Group, $F(1,46)=26.55$, $p< .001$. Neither the effect of Block, $F(5,230)= 2.35$, $p>.05$, nor the interaction $F(5,230)= .43$, $p>.05$ were significant. As shown in Figure 5, the Optimal Observation Group (*M* = .75, *SEM* = .07) made more diagonal moves following the discovery of a goal location as compared to the Random Observation Group (*M* = .24, *SEM* = .07). These results suggest that the Optimal Observation Group was making more moves consistent with the pattern as compared to the Random Observation Group from the beginning of the experiment and maintained this difference throughout the duration of the experiment.

Proportion of First Moves that Conform to the Optimal Search Strategy

A two-way mixed ANOVA on mean proportion of first moves that conform to the optimal search strategy with group (Optimal Observation, Random Observation) and Trial Block (1-6) as factors revealed a main effect of Group, $F(1, 46) = 21.29$, $p<.001$, and a significant Group x Block interaction $F(5,230)= 2.84$, $p< .05$. The effect of Block, $F(5,230)=.07$,$p= .99$ was not significant. The Group x Block interaction appears to be an artifact, as independent samples *t*-tests revealed significant differences between groups for all blocks, $ts(46) > 3.01$, $ps <.01$. In addition, the one-way repeated measure ANOVAs on the block factor for each group revealed no significance [Optimal Observation Group, $F(5, 115) = 1.22$, $p = .3$, Random Observation Group, $F(5, 115) = 1.93$, $p = 0.1$]. As shown in Figure 6, the Optimal Observation Group (*M* = .45, *SEM* = .06) engaged in a higher proportion of first moves conforming to the optimal search strategy as compared to the Random Observation Group (*M* = .07, *SEM* = .06). These results suggest that the Optimal Observation Group was making more first moves consistent with an optimal search strategy as compared to the Random Observation Group from the beginning of the experiment and maintained this difference throughout the duration of the experiment.

CHAPTER 4:

EXPERIMENT 1 DISCUSSION

The Optimal Observation Group demonstrated superior performance throughout each trial block, and this was demonstrated by the Optimal Observation Group engaging in fewer errors to complete a trial, fewer adjacent moves after discovery of a goal location, greater diagonal moves after the discovery of a goal location, and greater first moves consistent with an optimal search strategy compared to the Random Observation Group. Collectively, these results suggest observational learning in that participants completing the spatial pattern learning task who viewed a demonstrator completing the task in an optimal fashion outperformed participants who viewed a demonstrator completing the task in a random fashion. In short, results indicate that the type of strategy viewed prior to the completion of the spatial pattern learning task influenced the learning of the task.

It also appears that participants who watched a demonstrator complete the spatial pattern learning task in an optimal fashion may have adopted the same search strategy as the demonstrator. As a result, the observation of the optimal search strategy may have facilitated learning for participants in the Optimal Observation Group. Such a proposal would explain the significant differences between groups on all measures of the pattern learning task. However, it is also possible that the observation of the random search strategy may have inhibited learning for participants in the Random Observation Group. Such a proposal would also explain the significant differences between groups on all measures of the spatial pattern learning task. Finally, it is worth noting that some combination of facilitation for the Optimal Observation Group and inhibition for the Random Observation Group could have been operating simultaneously.

CHAPTER 5:

PURPOSE OF EXPERIMENT 2

Based on the findings in Experiment 1, that the Optimal Observation Group performed significantly better than the Random Observation Group, it remains unclear whether observation of an optimal strategy facilitated learning, observation of a random strategy inhibited learning, or some combination of facilitation and inhibition were acting simultaneously to produce group differences observed in Experiment 1. The purpose of Experiment 2 was to explicitly test these possibilities for group differences found in Experiment 1. Experiment 2 was identical to Experiment 1, but in addition to the Optimal Observation Group and Random Observation Group, a third (Control) group was added that experiences no opportunity for observation prior to the spatial pattern learning task. If facilitation of learning occurred, the Optimal Observation Group is expected to demonstrate superior performance across all variables of the spatial pattern learning task compared to both the Random Observation Group and the Control No Observation Group. If inhibition of learning impacted performance, the Random Observation Group is expected to demonstrate inferior performance across all variables of the spatial pattern learning task compared to both the Optimal Observation Group and the Control No Observation Group. Finally, if facilitation impacted participants in the Optimal Observation Group and inhibition impacted participants in the Random Observation Group, the Optimal Observation Group should outperform the Random Observation Group and the Control No Observation Group, but the Control No Observation Group should outperform the Random Observation Group.

CHAPTER 6:

EXPERIMENT 2 METHODOLOGY

Participants

Participants in this study were 108 (54 female, 54 male) undergraduate students different from those who participated in Experiment 1 at Georgia Southern University. Participants were recruited using an online experiment management system and received extra course credit for participation.

Apparatus, Stimulus, and Procedure

The apparatus, stimuli, and procedure are identical to Experiment 1 with the exception of the addition of a Control No Observation Group that did not watch a demonstrator before entering the virtual environment and completing the spatial pattern learning task. As a result, participants were randomly assigned to either the Optimal Observation Group (n=36), Random Observation Group (n=36), or Control No Observation Group (n=36). Gender was balanced both between and within groups.

CHAPTER 7:

EXPERIMENT 2 RESULTS

To determine the extent to which observational learning enhanced performance for the Optimal Observation group and/or diminished performance for the Random Observation Group relative to the Control No Observation Group, four separate two-way mixed ANOVAs were conducted on the following dependent variables: mean errors to complete a trial, mean proportion of adjacent moves following the discovery of a goal location, mean proportion of diagonal moves following the discovery of a goal location, and mean proportion of first moves conforming to the optimal pattern. The use of these variables allowed determination of group differences and the extent to which groups came under control of the spatial arrangement of goal locations.

Errors to Complete a Trial

A two-way mixed ANOVA on mean errors to complete a trial with Group (Optimal Observation, Random Observation, and Control No Observation) and Trial Bock (1-6) revealed a main effect of Block, $F(5, 525) = 50.44$, $p < .001$. Neither the effect of Group, $F(2, 105) = 4.59$, $p <.05$, nor the interaction $F(10, 525) = 1.49$, $p = .14$ were significant. As shown in Figure 7, the Optimal Observation Group (M = 10.22, SEM = 1.01) did not perform significantly different compared to either the Random Observation Group (M = 12.62, SEM = 1.01) or the Control No Observation Group (M = 13.06, SEM = 1.01). Post-hoc tests on the Trial Block factor are shown in Table 1.

Proportion of Adjacent Moves following the Discovery of a Goal Location

A two-way mixed ANOVA on mean proportion of adjacent moves following the discovery of a goal location with Group (Optimal Observation, Random Observation, and Control No Observation) and Trial Block (1-6) as factors revealed a main effect of Group, $F(2, 105) = 3.014$, $p = .05$ and a main effect of Block, $F(5, 525) = 3.81$, $p < .05$, although the interaction $F(10, 525) = .64$, $p = .783$ was not significant. Post-hoc tests on the Group factor revealed that the Optimal Observation Group differed significantly from both the Random Observation Group ($p < .05$) and the Control No Observation Group ($p = .05$), while the Random Observation Group and the Control No Observation Group did not differ significantly (p = .79). As shown in Figure 8, the Optimal Observation Group (M = .29, SEM = .07) engaged in fewer adjacent moves compared to both the Random Observation Group (M = .49, SEM = .07) and the Control No Observation Group (M = .52, SEM = .07). Post-hoc tests on the Trial Block factor are shown in Table 2. These results suggest that the Optimal Observation Group was making fewer moves that were inconsistent with the pattern as compared to both the Random Observation and Control No Observation groups from the beginning of the experiment and maintained this difference throughout the duration of the experiment.

Proportion of Diagonal Moves following the Discovery of a Goal Location

A two-way mixed ANOVA on mean proportion of diagonal moves following the discovery of a goal location with Group (Optimal Observation, Random Observation, and Control No Observation) and Trial Block (1-6) as factors revealed a main effect of Group, $F(2, 105) = 4.59$, $p < .05$ and a main effect of Block, $F(5, 525) = 24.99$, $p < .01$. The interaction $F(10, 525) = 1.49$, $p = .14$ was not significant. Post hoc LSD tests on the Group factor revealed that the Optimal Observation Group differed significantly from both the Random Observation Group ($p < .05$) and the Control No Observation Group ($p < .05$), while the Random Observation Group and the Control No Observation Group did not differ significantly ($p = .59$). As shown in Figure 9, the Optimal Observation Group (M = .64, SEM = .07) performed more diagonal moves after discovery of a goal location when compared to both the Random Observation Group (M = .43, SEM = .07) and the Control No Observation Group (M = .37, SEM = .07). Post-hoc tests on the Trial Block factor are shown in Table 3. These results suggest that the Optimal Observation Group was making more moves consistent with the pattern as compared to the Random Observation and Control No Observation Groups from the beginning of the experiment and maintained the difference throughout the duration of the experiment.

Proportion of First Moves that Conform to the Optimal Search Strategy

A two-way mixed ANOVA on proportion of first moves that conform to the optimal search strategy with group (Optimal Observation, Random Observation, and Control No Observation) and Trial Block (1-6) as factors revealed a main effect of Group, F (2, 105) = 7.726, $p < .05$, and a main effect of

Block, F (5, 525) = 2.710, $p < .05$. The interaction was not significant F (10, 525) = .35, $p = .97$. Post-hoc LSD tests on the Group factor revealed that the Optimal Observation Group differed significantly from both the Control No Observation Group ($p < .05$) and the Random Observation Group ($p < .05$). The Random Observation Group and Control No Observation Group did not differ significantly ($p = .7$). As shown in Figure 10, the Optimal Observation Group (M = .36, SEM = .05) performed more first moves consistent with an optimal search strategy as compared to both the Random Observation Group (M = .11, SEM = .05) and the Control No Observation Group (M = .16, SEM = .05). Post-hoc tests on the Trial Block factor are shown in Table 4. These results suggest that the Optimal Observation group was making more first moves consistent with an optimal search strategy as compared to both the Random Observation and Control No Observation Groups from the beginning of the experiment and maintained this difference throughout the duration of the experiment.

CHAPTER 8:

EXPERIMENT 2 DISCUSSION

The Optimal Observation Group appeared to demonstrate superior performance throughout each trial block compared to both the Random Observation Group and the Control No Observation Group, and this was demonstrated by the Optimal Observation Group engaging in fewer adjacent moves after discovery of a goal location, greater diagonal moves after the discovery of a goal location, and greater first moves consistent with an optimal search strategy compared to the Random Observation Group. In addition, the Random Observation Group and Control No Observation Group did not differ on these measures of spatial pattern learning. Although no group differences emerged with respect to mean errors to complete a trial, results collectively suggest not only did observational learning occur but also that participants completing the spatial pattern learning task who viewed a demonstrator completing the task in an optimal fashion facilitated learning of the task. As importantly, it also appears that participants completing the spatial pattern learning task who viewed a demonstrator completing the task in a random fashion did not inhibit learning of the task. As with Experiment 1, results indicate that the type of strategy viewed prior to the completion of the spatial pattern learning task influenced the learning of the task, and that participants who watched a demonstrator complete the spatial pattern learning task in an optimal fashion may have adopted the same search strategy as the demonstrator.

CHAPTER 9:

GENERAL DISCUSSION

Experiment 1, indicated by viewing the optimal search strategy compared to a random search strategy, produced differences in multiple measures of spatial pattern learning, including mean errors to complete a trial, mean proportion of adjacent moves following discovery of a goal location (i.e., search moves inconsistent with the diamond pattern), mean proportion of diagonal moves following discovery of a goal location (i.e., search moves consistent with the diamond pattern), and mean proportion of first moves that conform to the optimal search pattern. Collectively, these measures suggest that observation of the optimal search strategy facilitated performance and/or that observation of the random search strategy impaired performance. Experiment 2 tested this possibility by introducing a Control No Observation Group that did not view a digital avatar completing the spatial pattern learning task. Again, group differences emerged in multiple measures of spatial pattern learning, including trial, mean proportion of adjacent moves following discovery of a goal location (i.e., search moves inconsistent with the pattern), mean proportion of diagonal moves following discovery of a goal location (i.e., search moves consistent with the pattern), and mean proportion of first moves that conform to the optimal search pattern. Given that the Optimal Observation Group outperformed both the Random Observation and the Control No Observation groups, but the Random Observation and Control No Observation groups did not differ on these measures of spatial pattern learning, results collectively suggest that the observation of the optimal search strategy prior to the completion of the task enhanced performance for the Optimal Observation Group. Importantly, this suggests that observational learning occurred in the present set of experiments and that facilitation of learning in the Optimal Observation Group was the driving factor in the performance differences. These results have implications for how humans utilize information gathered from observations to both navigate an environment as well as complete tasks in their environment.

The Optimal Observation Group performed significantly better on all measures excluding mean errors to complete a trial in Experiment 2. Participants who watched an exemplary demonstrator complete the task utilizing an optimal search strategy learned the search task quicker and came under control of the hidden spatial pattern quicker than comparison groups in both studies. The Optimal Observation Group also engaged in a higher proportion of first moves that conform to the optimal strategy, which indicates that the observers were imitating the search strategy of the optimal demonstrator. All groups came under control of the hidden spatial pattern, although both the Control No Observation Group and the Random Observation Group failed to reach the same performance as the Optimal Observation Group. While facilitation of learning occurred, inhibition of learning did not appear to impact the performance of the Random Observation Group. Participants in the Random Observation Group did not show indicators of inhibition of learning. The performance of the Random Observation Group did not differ significantly from the Control No Observation Group who were required to utilize a trial-and-error learning strategy. These results indicate that participants in Random Observation Group likely utilized a similar trial-and-error search strategy instead of imitating the demonstrator utilizing a random search strategy.

These findings appear to be able to be explained within a theoretical framework found in social learning theory. Bandura (1971) suggested that observational learning produces changes in the observer based on the informative functions of the demonstrator's behavior. In this series of experiments, the optimal demonstrator's behavior appear to have provided the participants with useful information regarding the spatial pattern of the goals (diamond shape) and the optimal search strategy to use to get reinforcement. This information makes the observer more likely to attend to the demonstrator and remember the behaviors so they can be reproduced later. While the demonstrator for the Random Observation Group appears to have failed to provide useful information to the Random Observation Group as indicated by their performance.

Participants in the Random Observation Group witnessed the demonstrator receive more instances of punishment compared to participants in the Optimal Observation Group. These differences may have led the Random Observation Group participants to determine that the demonstrator lacked the necessary informative value to imitate. Instead, it appears that participants reverted to a trial-and-error search strategy as indicated by the similar performance of both the Random Observation and Control No Observation groups. The repeated exposure to punishment may have also decreased the status of the demonstrator, which would have also decreased the likelihood of the participant imitating the search strategy of the demonstrator. The similarity in performance of the Random Observation Group and the Control No Observation Group is important to note because it suggests that humans do not indiscriminately imitate the behaviors of a conspecific. If the strategy of the demonstrator is inefficient or uninformative, it appears that participants utilized other strategies to complete the task. This ability is indicative of a cognitive process controlling imitation in humans which could have evolutionary significance. If humans were to indiscriminately imitate without consideration for the consequences of the demonstrator's behavior, then it may be more difficult for humans to engage in novel behaviors, ceasing self-injurious behaviors, or learning how to interact with novel social groups.

Results from the two experiments provide evidence to suggest that the human participants come under control of a hidden spatial pattern, which is consistent with the work Brown and colleagues have conducted with rodents (Brown, 2006). Utilizing a similar search task, Brown and colleagues found that rodents can come under control of hidden spatial patterns made up of multiple shapes, including a 2 x 2 square and line (Brown & Terrinoni, 1996), as well as a checkerboard pattern (Brown, Zeiler, & John, 2001). Current results are also consistent with the findings from Keller and Brown (2001) and Brown, Farley, and Lorek (2007) that the behavior of a rat is influenced by the observation of a conspecific. Collectively, current results are also consistent with the observational learning phenomenon literature concerning non-human animals, and the current experiments also provide evidence to suggest that humans engaged in observational learning as they came under control of a hidden spatial pattern more rapidly after observing a demonstrator complete the search task in an optimal fashion. Results from the current experiments are also indicative of facilitation of learning within the Optimal Observation Group.

In conclusion, it appears that humans are affected by observational learning in a spatial pattern learning task in a virtual environment, and results appear capable of being explained within a social learning theory context. Although participants did not interact nor compete for resources with the demonstrator, future studies may address such conditions by adding a confederate digital avatar into the virtual environment and allowing the participants to complete a search task while the confederate digital avatar engages in a set pattern of moves. This would help elucidate the ability of humans to adjust search strategies in real time while interacting with a conspecific under varying conditions.

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TABLES AND FIGURES

Table 1

	Block 1	Block 2	Block 3	Block 4	Block 5	Block 6
Block 1	---	***	***	***	***	***
Block 2		---	**	**	***	***
Block 3			---	*ns*	*ns*	*
Block 4				---	*	*
Block 5					---	*ns*
Block 6						---

Note. *ns* = not significant. * = $p < .05$. ** = $p < .01$. *** = $p < .001$.

Table 1. Post-Hoc Tests for the Block factor of Experiment 2 for Errors to Complete a Trial.

Table 2

	Block 1	Block 2	Block 3	Block 4	Block 5	Block 6
Block 1	---	*ns*	*ns*	*ns*	*	*
Block 2		---	*ns*	*ns*	*	*
Block 3			---	*ns*	*ns*	*ns*
Block 4				---	*	*
Block 5					---	*ns*
Block 6						---

Note. *ns* = not significant. * = $p < .05$. ** = $p < .01$. *** = $p < .001$.

Table 2. Post-Hoc Tests for the Block factor of Experiment 2 for Mean Proportion of Adjacent Moves following the Discovery of a Goal Location.

Table 3

	Block 1	Block 2	Block 3	Block 4	Block 5	Block 6
Block 1	---	***	***	***	***	***
Block 2		---	**	**	***	***
Block 3			---	*ns*	*	**
Block 4				---	*	**
Block 5					---	*ns*
Block 6						---

Note. *ns* = not significant. * = $p < .05$. ** = $p < .01$. *** = $p < .001$.

Table 3. Post-Hoc tests for the Block Factor of Experiment 2 for Mean Proportion of Diagonal Moves following the Discovery of a Goal Location.

Table 4

	Block 1	Block 2	Block 3	Block 4	Block 5	Block 6
Block 1	---	*ns*	*ns*	**	**	*ns*
Block 2		---	*ns*	*ns*	*ns*	*ns*
Block 3			---	*ns*	*ns*	*ns*
Block 4				---	*ns*	*ns*
Block 5					---	*ns*
Block 6						---

Note. *ns* = not significant. * = p < .05. ** = p <.01. *** = p < .001.

Table 4. Post-Hoc tests for the Block Factor of Experiment 2 for Mean Proportion of First Moves Conforming to the Optimal Search Strategy.

Figure 1

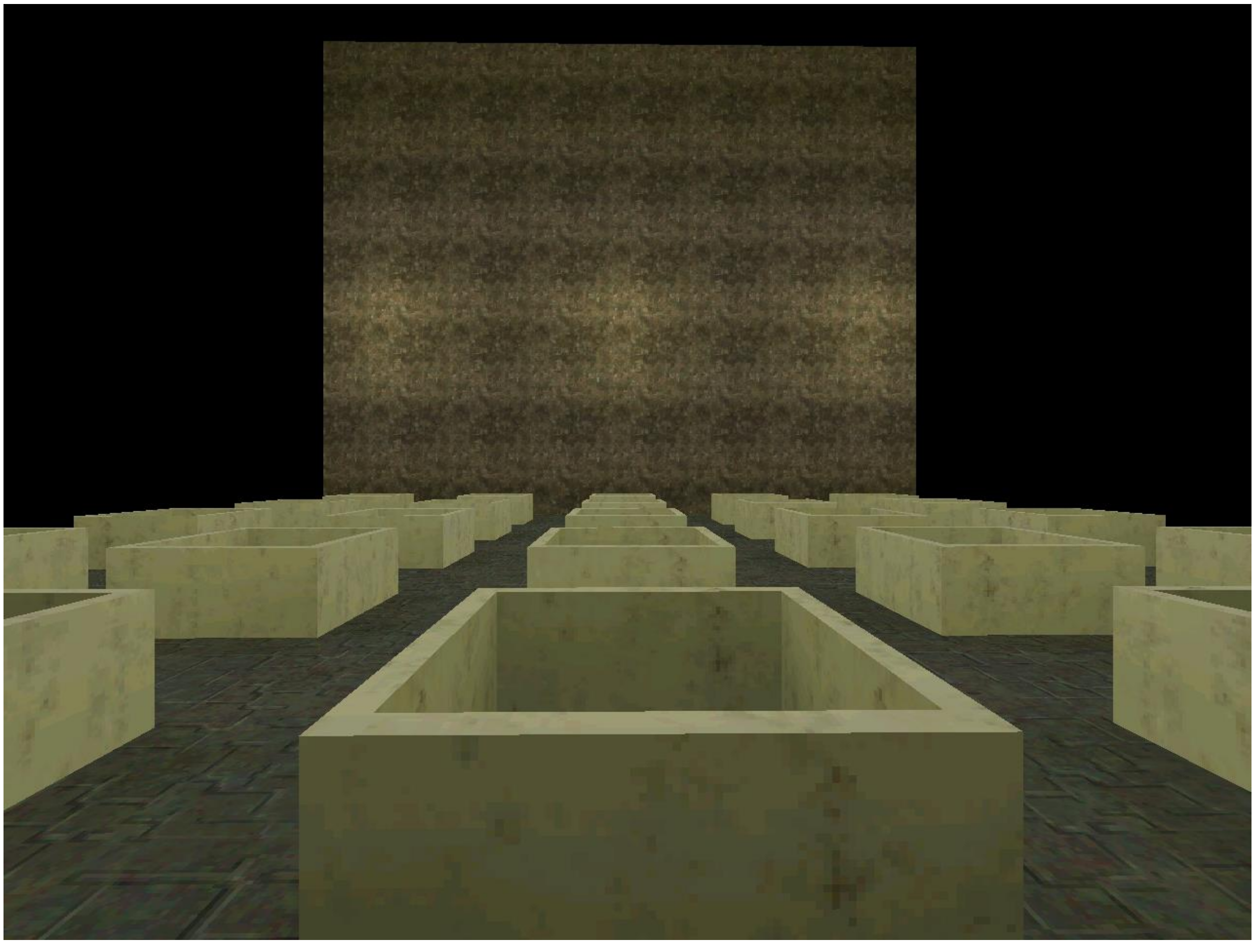

Figure 1. First Person View of the Virtual Environment Viewed from the Starting Location.

Figure 2

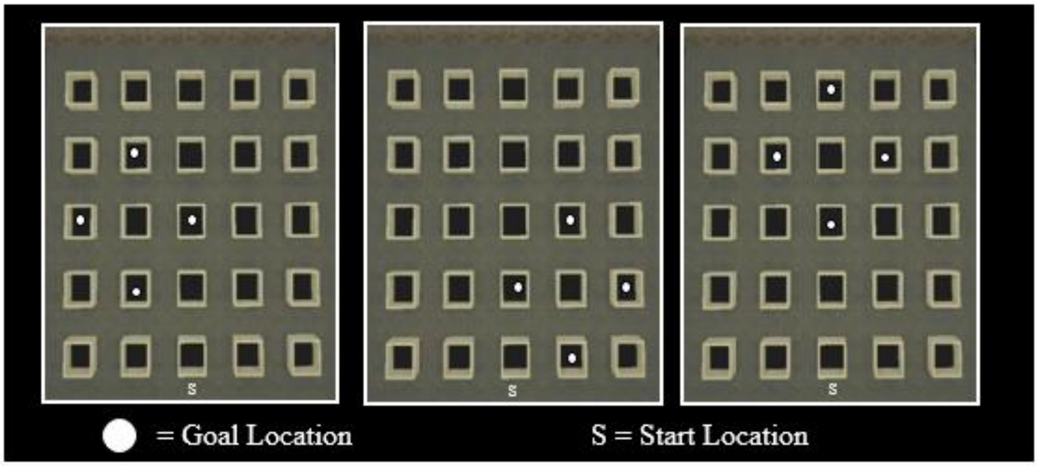

Figure 2. Overview of the Virtual Environment (The “s” designates the starting location. The goal locations are denoted by the white dots.)

Figure 3

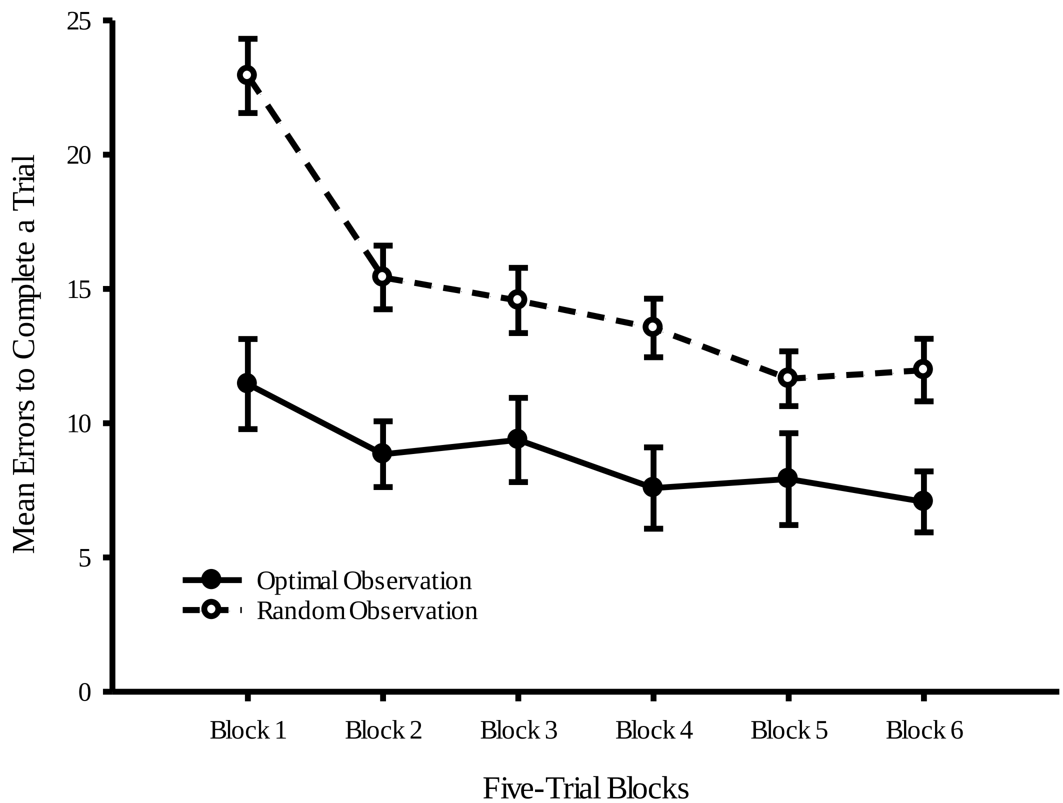

Figure 3. Mean Number of Errors to Complete a Trial, plotted by Five-Trial Blocks for each group. Error bars represent standard errors of the means.

Figure 4

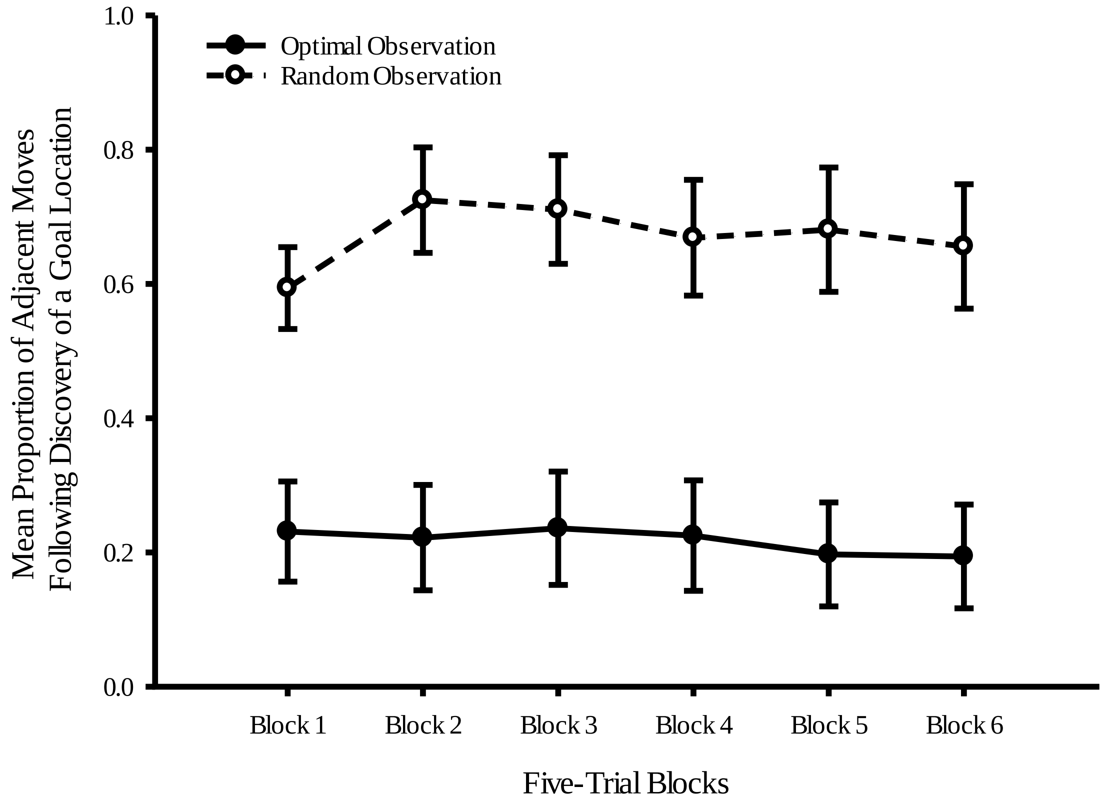

Figure 4. Mean Proportion of Adjacent Moves following Discovery of a Goal Location, plotted by Five-Trial Blocks for each group. Error bars represent standard errors of the means.

Figure 5

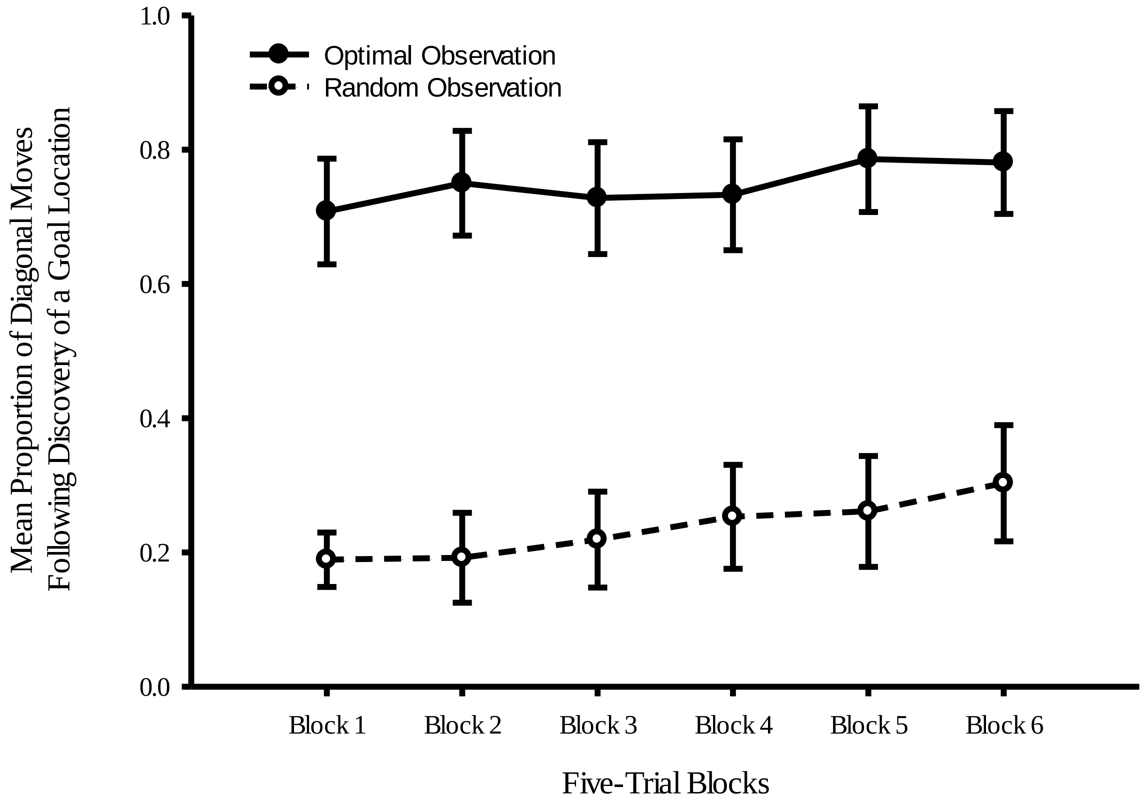

Figure 5. Mean Proportion of Diagonal Moves ollowing Discovery of a Goal Location, plotted by Five-Trial Blocks for each group. Error bars represent standard errors of the means.

Figure 6

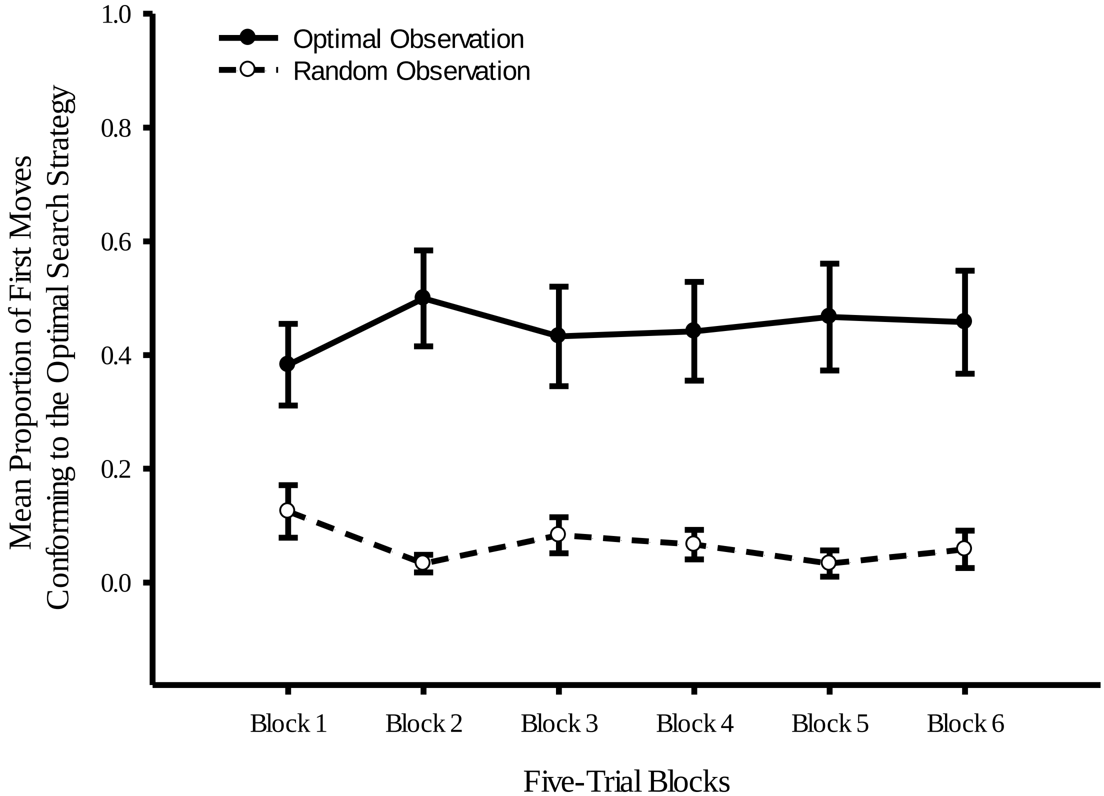

Figure 6. Mean Proportion of First Moves Conforming to an Optimal Search Strategy, plotted by Five-Trial Blocks for each group. Error bars represent standard errors of the means.

Figure 7

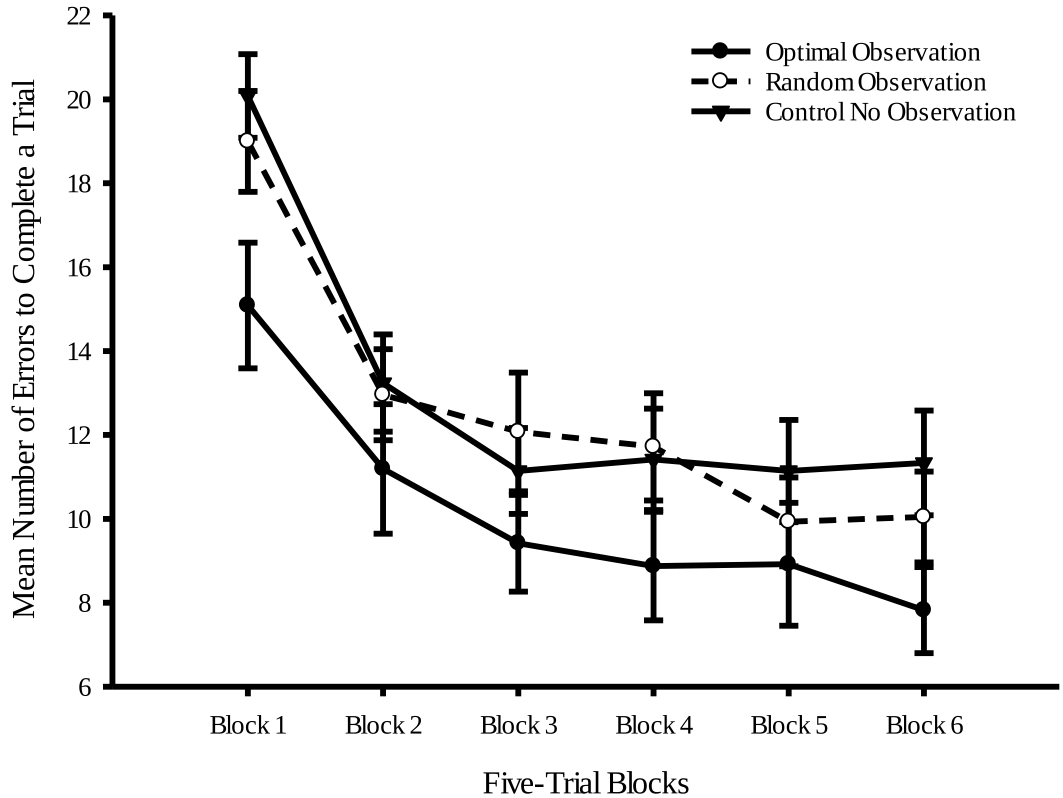

Figure 7. Mean Number of Errors to Complete a Trial, plotted by Five-Trial Blocks for each group. Error bars represent standard errors of the means.

Figure 8

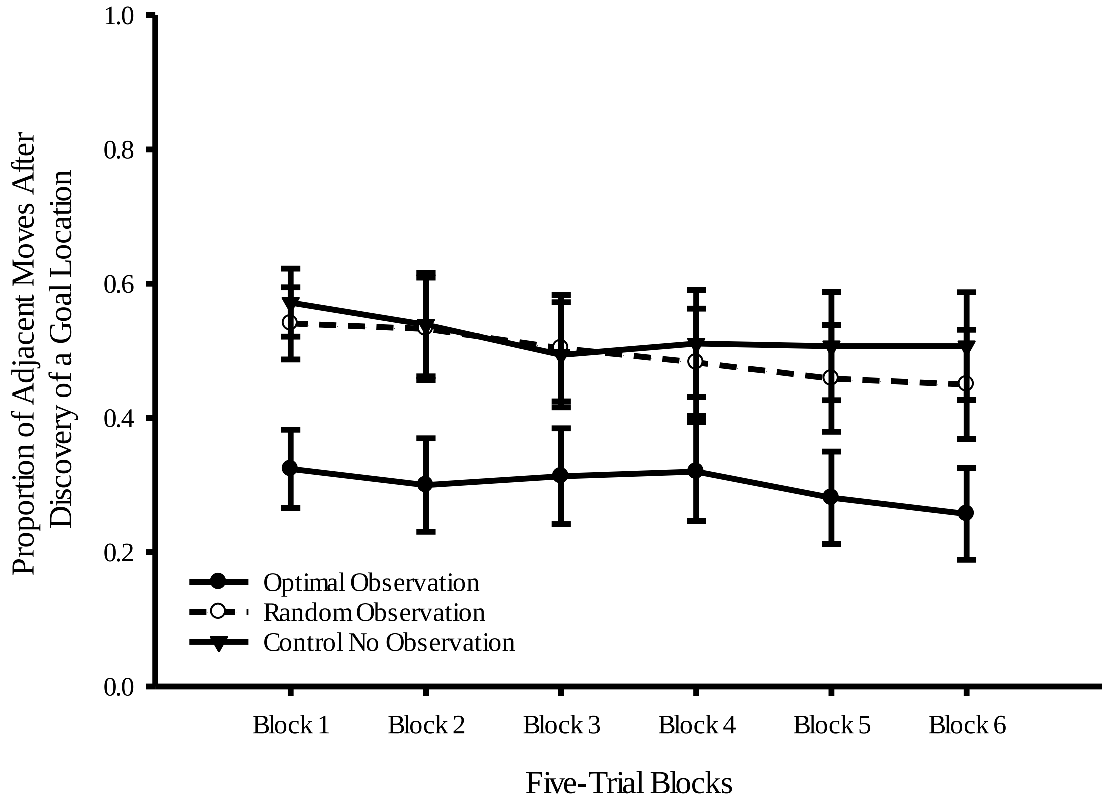

Figure 8. Mean Proportion of Adjacent Moves following Discovery of a Goal Location, plotted by Five-Trial Blocks for each group. Error bars represent standard errors of the means.

Figure 9

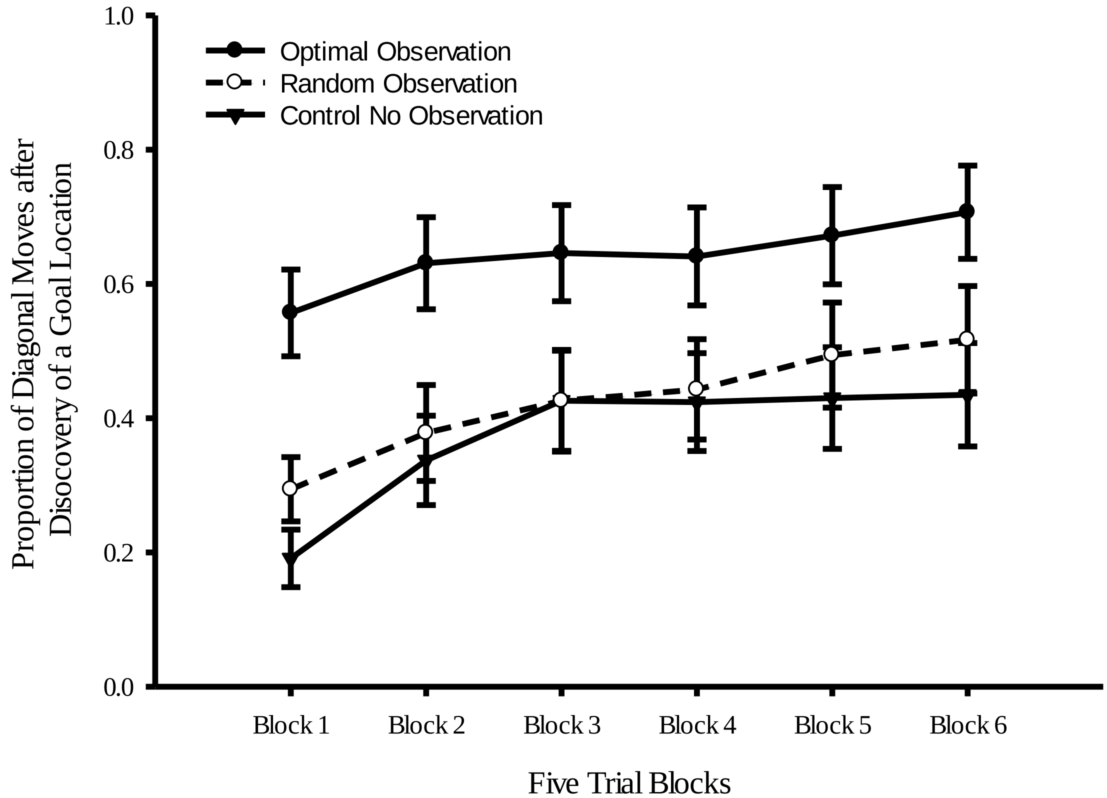

Figure 9. Mean Proportion of Diagonal Moves following Discovery of a Goal Location, plotted by Five-Trial Blocks for each group. Error bars represent standard errors of the means.

Figure 10

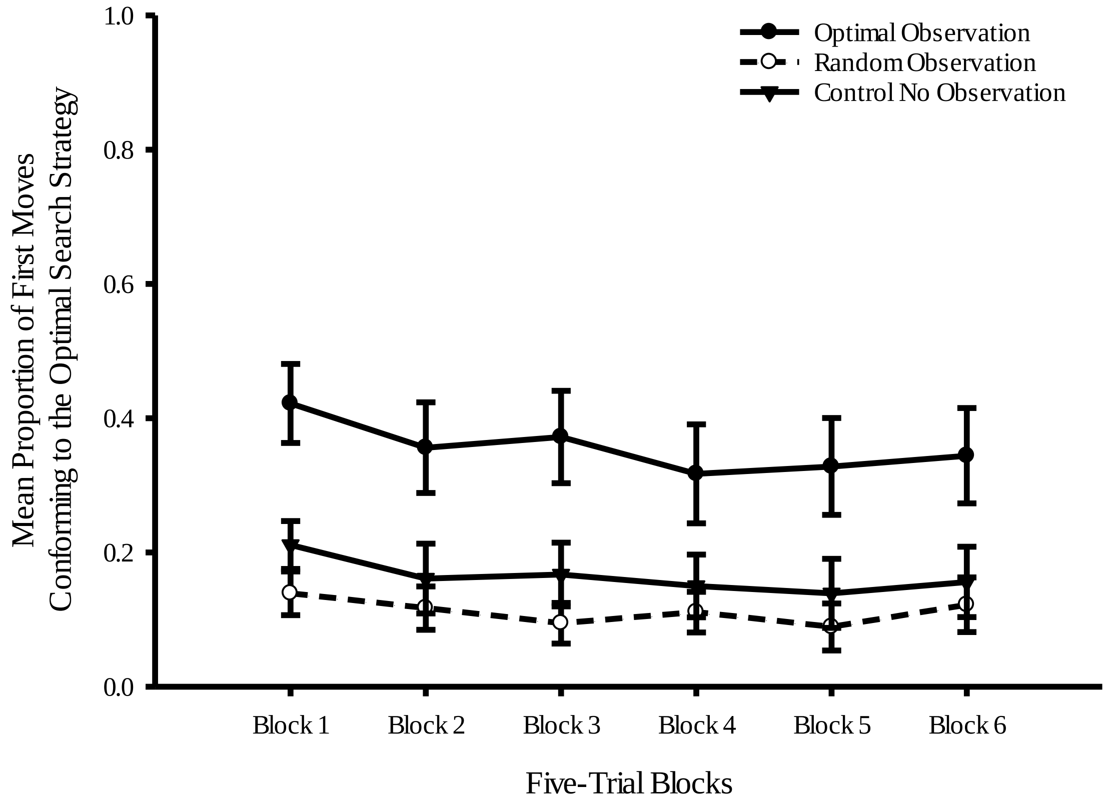

Figure 8. Mean Proportion of First Moves Conforming to an Optimal Search Strategy, plotted by Five-Trial Blocks for each group. Error bars represent standard errors of the means.