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The Effects of Viewpoint, Motion, and Affordance Priming on Perceptual Learning of Feelies

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THE EFFECTS OF VIEWPOINT, MOTION, AND AFFORDANCE PRIMING ON PERCEPTUAL LEARNING OF FEELIES

by

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ABSTRACT

According to Gibson and Gibson (1955) perceptual learning is a process of developing the skill to differentiate previously undifferentiated but available information. The initial investigations focused on object identification, lacking a behaviorally relevant functional task. In the current study participants learned to differentiate between novel objects (feelies). To test the role of visual exploration objects were viewed from either a side or a top view and were displayed as either static pictures or rotating about a vertical axis. In Experiment 1 a simple object discrimination task was used. Perfect accuracy was achieved sooner in static conditions compared to motion conditions regardless of viewpoint, suggesting that visual exploration was not necessary. Experiment 2 investigated if a functionally relevant task would necessitate the usage of exploratory activity for perceptual learning. Three priming conditions were included to provide task contexts of varying behavioral relevance. Participants were required to 1) think of potential uses (i.e., affordances) for the feelies, or 2) think of one specific use provided by the experimenter, or 3) were asked to describe the object’s physical appearance using semantic labels. The opportunity to visually explore objects in varied ways benefited learning the most in the condition in which observers had to come up with potential uses for the objects. This prime promoted functionally relevant, deep levels of processing. The most efficient and stable pattern of learning was observed when participants actively generated uses for moving objects that were shown from the side view. It was concluded that exploratory activity facilitates perceptual learning of affordances.

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LIST OF ABBREVIATIONS

3D	Three-dimensional
GA	Generated Affordance
GS	Generated Semantic
PA	Provided Affordance
PLA	Polylactic Acid
RT	Response Time
USM	The University of Southern Mississippi

CHAPTER I – Introduction

"The world is so full of a number of things, I'm sure we should all be as happy as kings." This quote from writer and poet Robert Louis Stevenson perfectly embodies the incredibly complex and diverse world we live in; so full of innumerable sights, smells, sounds, and events that we are never left wanting for stimulation. From the moment of birth to death, we are constantly experiencing a plethora of sensations from ourselves and all that is around us. This flow of information is so continuous and ubiquitous that we never stop to consider how or when we came to perceive these things. When did you first realize that a cup was not the same object as a bowl? How did you come to recognize that a steak knife was different from a butter knife? We take for granted that we know these things now but spare little thought to what it would mean if we had never acquired this knowledge.

Perceptual learning can be thought of as the improvement of perception from experience (learning to perceive), and the acquisition of knowledge as a function of changes in perception (perceiving to learn; Pick, 1992). These changes in perceptual abilities and knowledge allow us to better function in our environment by improving our ability to guide actions, perform tasks efficiently, and focus on relevant information (Gibson & Pick, 2000). Failure to develop these skills would essentially limit us to the capabilities of a young infant. Understanding the process of perceptual learning is necessary to comprehend and appreciate human development. Additionally, perception and perceptual learning can be thought of as a life-long process, allowing us to continually adjust and coordinate with our environment (Szokolszky et al., 2019), so perceptual learning is relevant to anyone of any age.

The goal of the current project was to examine perceptual learning of objects that are entirely novel and free from any experiential bias. Participants performed a discrimination task in which they observed a set of ten objects (feelies) that were either rotating or stationary from different viewpoints and determined if each object is the same as, or different from a target object. In addition, I investigated if associating novel objects with a potential use would enhance perceptual learning.

The theorized involvement of learning and experience in perception can be traced back to Hermann von Helmholtz and his theory of perception. Like the Gestalt theorists, Helmholtz (1911) believed that perception was more than the sum of our sensations; the stimuli in our environment are impoverished compared to the information-rich perceptions we experience, and therefore required additional mental processing to become meaningful. However, unlike the Gestalt theorists, Helmholtz did not believe that perception relied solely on innate principles. Helmholtz diverged from the traditional views of perception by making learning an essential aspect of his theory of perception. According to this theory, perceived properties of distal stimuli (e.g., object's size and distance) are subject to unconscious inferences based on specific contingencies learned from the world (i.e., experience). The present contribution focused on the ecological theory of perceptual learning (Gibson & Gibson, 1955) which was in sharp contrast with Helmholtz's approach.

The ecological theory of perceptual learning was created in response to the rise in popularity of cognitive theories of learning and their shared belief that perception necessitated the involvement of complex cognitive processes such as thinking, problem-solving, language, concept formation, information processing, and other internal mental structures because the information about environmental stimuli received through sensory organs is impoverished, incomplete, and insufficient to explain the rich perceptions we experience. Therefore, these impoverished stimuli required enrichment and structuring in the form of additional processing (e.g., association from experience), which serves to supplement the sensations (Ertmer & Newby, 2013; Gibson & Pick, 2000; Lobo, 2019).

Unconvinced that stimuli were impoverished and required supplementation from cognitive processing to be meaningful, James and Eleanor Gibson created an alternative theory based on their belief that perception does not require any additional mental processes such as representation, memory, and association because "the world is enough" (i.e., stimuli provide enough information for the perceptions we experience without supplementation from cognition). According to the ecological theory of perceptual learning (Gibson & Gibson, 1955), information is ample and structured, able to fully specify the layout, surfaces, objects, and events of the environment. Perceptual learning occurs because perception begins as unrefined and inefficient. Before perceptual learning, information is overly generalized, and attention is not selective enough (Gibson 1961, 1963; Gibson & Pick, 2000). Learning reduces generalization among stimuli, increases precision of discrimination, and allows previously undetected (i.e., undifferentiated) variables or distinctive features to be detected and utilized. Perception, therefore, is not a process of enriching or adding to the input from the environment, but of differentiating the information that is already available (Gibson & Gibson 1955; E. Gibson, 1961, 1963, 1969; J. J. Gibson, 1979).

As a test of their theory of perceptual learning, Gibson and Gibson (1955) conducted a study in which children and adults were shown a series of drawings called “scribbles”. Seventeen spring-like coiled scribbles varied from each other on different dimensions (e.g., number and spacing of coils, and direction of coiling of each scribble) but were ultimately very similar to each other and were intended to be initially indistinguishable from one specific coil-like scribble that was identified as the critical item. Another set of twelve scribbles were less coil-like and more closely resembled basic shapes (e.g., triangle, bullseye, heart), and were intended to be distinguishable from the critical item at the beginning of the study (see Figures 1 & 2 on pg. 36 of Gibson & Gibson, 1955). Participants were presented with the critical item for five seconds, told it was the critical item, and that they asked to identify it as such each time they saw it presented. They then viewed a series of cards on which 34 scribbles were presented for three seconds each. During each session of presentations, the critical item was presented four times interspersed with 30 other, non-critical scribbles. After these 34 presentations, the critical item was presented again for five seconds. Participants were asked to report which items were the same (i.e., the critical item) by giving identifying responses such as "that’s it" or "this is the one I saw before” when shown items they perceived to be the critical item. These sessions of 36 trials continued (item order randomized) until participants identified only the four presentations of the critical item as being the same (100% accuracy). No feedback was provided by the experimenter during this experiment. The results of the study showed that adults and children 8.5 to 11 years old were able to reach 100% accuracy within an average of 3.1 and 4.7 sessions, respectively, demonstrating that repeated exposure to stimuli alone (i.e., without supplementation from cognitive processing such as association or cues) was enough for participants to learn to differentiate between initially indistinguishable stimuli to the point that they were able to identify the critical item from all other items with perfect accuracy.

The Gibsons continued to develop the ecological theory of perception and perceptual learning by elucidating the nature of the information perceived and how we utilize this information to improve our perception through learning. In the current ecological theory (Gibson, 1979), perception is thought to be direct in the sense that perception is the detection of the information that is actually present in the environment, and that no intermediary representations or cognitive processes are needed to connect the environment and our perception of it. Information is conceptualized as energy patterns in space and time that specify states and behaviors in the organism-environment system. Therefore, because information is specific to an environmental state of affairs and perception is specific to the information, perception is specific to the environmental state of affairs (i.e., direct; Michaels & Palatinus, 2014). All the information about the environment (including events that take place within the environment) is present in ambient arrays of energy surrounding an organism (Gibson, 1979), which must be explored by perceptual systems to extract useful information for the organism.

Perceptual learning teaches us how to narrow down the abundance of information from the environment to the optimal information needed. Originally, perceptual learning considered this optimal information to be distinctive features (Gibson, 1969), but Eleanor Gibson later expanded the theory to include actions, aligning with James Gibson's (1979) concept of perception-action cycles, in which perceiving defines what is available for acting and acting defines what is available to perceive. Consequently, the purpose of perceptual learning was adapted to be the attainment of information that specifies the properties and affordances of an event, object, or layout, in pursuit of goal-oriented actions (Gibson & Pick, 2000; Gibson, 2003).

Having established "what" we learn through perceptual learning, we should now briefly explain "how" perceptual learning is accomplished. According to Gibson (1969; 2000), differentiation occurs through a process known as the "education of attention". This is an action-based process involving active search and exploration, through which the organism becomes more selective about what information it seeks out and uses, focusing attention on the most relevant information for exploring, guiding action, and performing tasks more efficiently. This echoes James Gibson's theory that all perception is an active process that detects information through exploratory and performatory actions (Gibson, 1962; 1963). Exploratory activity provides information about both the environment and the capabilities of the organism (Gibson, 1979). The better informed about the environment and itself, the better the organism can direct its attention and actions efficiently, and the better suited it is to its environment.

One way that information is collected from the environment is through visual perception. Visual perceptual learning has been observed in tasks such as detection or discrimination of visual gratings (De Valois, 1977; Fiorentini & Berardi, 1980), stimulus orientation judgment (Dosher & Lu, 1998; Petrov et al., 2006), hyperacuity and vernier tasks (Fahle & Edelman, 1993; Poggio et al., 1992), motion direction discrimination (Ball & Sekuler, 1982), and judgments of object mass from collision (Jacobs et al., 2001). Surprisingly, there exists little research on the type of stimuli that we encounter early in life and purposely interact with every day of our lives: objects. Some of the first things we see in infancy are objects (i.e., toys, bottles, household furniture) and we continually utilize objects throughout our lives to help us accomplish large and small goals (e.g., spoons, tv remotes, bars of soap, cars). Both common (Chen & Op de Beeck, 2021; Furmanski & Engel, 2000) and novel objects (Gauthier & Tarr, 1997a; Gauthier et al., 1998; Norman et al., 2004) have been used in perceptual learning and discrimination studies. However, learning of common objects can be complicated by previous experience and general familiarity.

The objects to be used as stimuli in the current study (feelies) have never been used in a learning task and are sufficiently similar yet distinguishable, making them well-suited for a discrimination task. Feelies are completely novel, having been designed specifically to be unlike any common object (Caviness, 1962). However, feelies are similar to many of the everyday objects we encounter in the sense that they are neither too complex nor too simple. This means that feelies are more ecologically valid than basic geometric stimuli (e.g., lines; Matthews & Welch, 1997; geons, see Biederman & Bar, 1999) or very complex but highly specific stimuli (e.g., faces; Gold et al., 1999). These characteristics make feelies ideal stimuli for studying object learning.

In addition to object characteristics, visual perception (and, by extension, visual perceptual learning) can also be greatly influenced by the conditions in which viewing occurs. A wide range of environmental factors such as radiant and ambient lighting, distance, slant/tilt, motion, and perspective/point of view can comprise viewing conditions and affect visual perception. As mentioned previously, according to the ecological view, learning and perception are active processes in which the learner/perceiver seeks out and utilizes information from the environment to inform actions (Gibson, 1962; 1963; 1969). In the active process of visually exploring objects, we are apt to move either the object in relation to ourselves (if the object affords handling), or ourselves in relation to the objects (such as when a large or heavy object is viewed). In either instance, motion creates systematic transformations of visual information such as object shading, texture gradients, specular highlights, and boundary contours, which can be used to specify 3D shape (Todd, 2004). Additionally, movement allows for the presentation of multiple viewpoints (i.e., perspectives), each of which displays unique depths and orientations of every visible surface point, causing different images of shapes to be projected to the retina as viewing position changes (Hayward, 2003; Todd, 2004). As such, the ability to sample visual scenes dynamically by assuming many viewpoints is essential to active exploration.

Although motion and viewpoint are potentially rich sources of information for visual perception, research on their influence is mixed. Compared to static conditions, movement of stimuli (typically rotation in depth) is often beneficial to visual perception of 3D shape. Movement has been shown to produce improvements in object recognition and discrimination (Norman, Bartholomew et al., 2008; Norman et al., 2000), and judgments of ordinal depth (Norman & Raines, 2002) and surface orientation (Norman et al., 1995). However, some findings indicate that human observers have difficulty making full use of the information provided by movement, such as making large systematic errors when judging 3D metric structure from moving or stereoscopic displays (Norman et al., 1996; Todd, 2004; Todd & Norman, 2003). While small changes in perspective from movement (e.g., freely moving the head; ≈10°) are insufficient (Lind et al., 2003), when continuous perspective changes of 45° or more are experienced, metric shape can often be perceived (Bingham & Lind, 2008; Lind et al., 2014). Furthermore, perception of metric shape can be used to inform object recognition (Lee at al., 2012) and improve functional tasks such as reaches-to-grasp (Lee & Bingham, 2010).

Viewing an object from multiple perspectives provides rich information about 3D shape and structure. However, changes in viewpoint can also cause difficulties in object recognition and shape constancy (Gauthier & Tarr, 1997b; Gauthier et al., 1998; Norman, Bartholomew et al., 2008; Norman et al., 2000; Tarr, 1995; Tarr & Pinker, 1989; Todd & Norman, 2003). These issues likely arise because one object, when viewed from different perspectives, will project different shapes onto the retina. Individuals may not recognize that these different images all belong to the same object and, instead, perceive each image as belonging to different objects. Despite findings that perception of objects is often viewpoint dependent, most objects can be accurately recognized as the same when presented in different orientations (Biederman & Bar, 1999; Biederman & Gerhardstein, 1993). For example, Shepard and Metzler (1971) found that observers were 96.8 percent correct in classifying objects as the same or mirror images of each, regardless of the orientation differences. Furthermore, there is some evidence that certain viewing perspectives may be advantageous in contexts such as 3D shape perception from surface texture (Ware & Sweet, 2004) and decision-making in sports (Mann et al., 2009).

One purpose of the proposed experiment was to elucidate the nature of perceptual learning of ecologically valid objects and examine the influence of motion and viewpoint on learning. Rate of learning, discrimination sensitivity, and response time were used to assess learning in an object discrimination task. Objects were viewed from either a side or a top view and were displayed as either static or moving (rotating about a vertical axis). To the extent that perceptual learning is affected by the presence of motion and/or viewpoint differences in one or all of these measures were expected between conditions.

Any account of learning according to the ecological theory of perception would be incomplete without the inclusion of affordances. Affordances are possibilities for action, what the environment offers the animal when both the physical properties of the environment and the bodily capabilities of the organism are considered. Gibson (1979) asserted that affordances are the primary properties that we perceive. Therefore, we do not only learn to perceive physical properties of objects, like size, shape, or distance for their own sake, we perceive functional relations between objects, ourselves, and the world around us (Adolph & Kretch, 2015; Gibson & Pick, 2000). Studies of affordance learning often focus on infants (Gibson, 1982; Gibson & Walker, 1984) or robotics (Lopes et al., 2007; Montesano et al., 2008; Sun et al., 2010). A difficulty that arises with studying object affordance learning is that we are often already familiar with the affordances of many common objects, or the affordances are easily detected upon initial investigation because most human-made objects are created with the intention to serve specific purposes (Dennett, 1987) and therefore usually have salient designed affordances (Rachwani et al., 2020). As novel objects, feelies have no obvious or predetermined functions but can still be associated with many potential uses and functions (Dowell et al., 2020).

In the second experiment it was hypothesized that a functional description of an object should enhance perceptual learning because everyday perception typically involves perceiving the affordance properties of objects, and not simply perceiving shape for its own sake. Because perception is a process of directly detecting meanings for action and not a matter of simply assigning meaning to objects with certain physical properties, associating objects with a functional use (affordance) will likely facilitate faster learning compared to learning based on object shape or physical appearance (color, texture, etc.).

Several hypotheses were tested in the present contribution. First, perceptual learning was expected to be faster and more accurate when there are opportunities to explore objects from multiple viewpoints (H1). This hypothesis was tested in two ways: By having the stimulus either move or be static (H1A), and by viewing the stimulus from the side or from the top (H1B). It was predicted that perceptual learning should be faster and more accurate when the stimulus is viewed from the side as opposed to from the top, and when the stimulus is moving as opposed to being static. Second, perceptual learning was expected to be faster and most accurate when the task involves thinking about potential uses as opposed to simple discrimination (H2). Specifically, perceptual learning should be the fastest and most accurate when participants are forced to think of potential uses for the objects as opposed to when they are primed to think about a specific use provided by the experimenter, or when they are simply asked to describe the object's physical appearance. Viewing a rotating object from a side view while actively thinking about what it can be used for should be the optimal combination of factors leading to fastest and most accurate learning.

CHAPTER II – Experiment I: Perceptual Learning of Feelies

The present experiment tested the influence of viewpoint and motion on the perceptual learning of novel shapes in an online experiment. Ten feelies served as stimuli and were presented either from above (a relatively unfamiliar viewpoint) or from the side (simulating the perspective of an observer seated at a table). Objects were presented as either rotating about a vertical axis on a rotating podium or statically against a white background. According to Gibson (1988) exploratory activity is necessary for perceptual learning to occur. Rotations around a vertical axis supply opportunities to sample the information that specifies an object from multiple viewpoints. Additionally, a side view provides an egocentric viewpoint that is typically encountered when viewing objects in activities of daily life. Thus, it was hypothesized that moving stimuli observed from the side would facilitate perceptual learning most effectively.

2.1 Participants

Participants were 302 undergraduates at the University of Southern Mississippi (USM) who were at least 18 years old. All participants possessed normal or corrected to normal eyesight. Participants were recruited through USM's SONA participant pool. All experimental procedures were reviewed and approved by USM's Institutional Review Board (IRB) to adhere to the ethical treatment of human subjects. Data from 67 participants was excluded due to incompleteness (participants did not complete the full experiment). Sixty participants completed the study in its entirety but failed to reach the learning criterion (100% accuracy) during the experiment. Consequently, data from these participants was not analyzed for accuracy and reaction time with the 175 participants who successfully reached criterion. However, data from participants who failed to reach criterion was examined using survival analysis.

A sensitivity analysis using G*Power (Erdfelder et al., 1996) with 0.80 power, estimated that a sample size of 200 would be needed to detect effect sizes that were small-to-medium (Cohen's d = 0.5 - 0.8). The choice to use 175 participants was based on the fact that each participant completed several trials as they progressed through learning blocks. Each participant who completed the study experienced 176 test trials (22 per block over 8 blocks). Compared to Gibson and Gibson (1955), in which adult participants required an average of 105 test trials to reach the 100% accuracy criterion used in this study, the number of trials per participants has been increased, which can reduce the overall number of participants needed in a study without sacrificing power and has the additional benefit of reducing within-subjects variance (Baker et al., 2021). Previous studies using same-different discrimination tasks have utilized this design (Dowell et al., 2018; Norman et al, 2004; Norman et al, 2012; Petrov et al., 2006) with as few as 9 participants per group when each person completed 120 trials (Norman, Clayton et al., 2008).

2.1.1 Demographics

Participants were primarily young adults (*M* = 22.17, *SD* = 6.64). The majority of participants identified as female (N = 204), with a smaller portion identifying as male (N = 31). Self-report data of participants' racial identities shows that most participants were White (N = 154), but the sample also included Black (N = 62), Asian (N = 13), American Indian (N = 2), and Other (N = 4) individuals.

2.2 Materials

The stimuli used in this study were high-quality digital images and videos of copies of the ten original feelies (Gibson, 1962). The original feelies were three-dimensionally scanned by Phillips and Egan (2016). Using these scans, copies were printed via a Tevo Tarantula 3D printer using polylactic acid (PLA) for use in the present study (see Figure 1 below). All feelies have a slightly different shape, but the topological configuration is identical. This means that all objects have a smooth surface curvature all throughout and six identifiable apexes of varying proportions. The mass and volume of all objects is comparable with minimal variability.

2.3 Measures and Data Collection

Demographics, including age, race, and gender were collected via computer responses at the start of the experiment. Normal or corrected-to-normal visual acuity of all participants was confirmed via self-report by having participants affirm that they have normal or corrected-to-normal (e.g., corrective lenses) vision. Response times for each trial were recorded via the Collector (Garcia et al., 2015) software.

2.4 Design

The independent variables in this study were Viewpoint, Motion, and Block. Viewpoint was between-subjects with two levels: side view or top view. Motion was also between-subjects with two levels: static or moving (rotating about a vertical axis). Participants were randomly assigned to a Viewpoint and a Motion condition, with a comparable number of participants assigned to each condition (Top-Motion $n = 40$; Top-Static $n = 45$; Side-Motion $n = 41$; Side-Static $n = 49$). Each participant was presented stimulus objects in a series of eight learning blocks. For each participant, one of the ten feelies was randomly selected as the target object. The target object remained the same throughout the experiment for each participant but the specific feelie assigned as the target varied between participants. The order in which each feelie was assigned as the target item was counterbalanced between conditions, with each feelie being selected at least four times within each condition in a randomized order. Each learning block consisted of 23 total trials: 1 presentation of the target object (study trial), followed by 22 experimental trials where the nine feelies that are non-targets were presented twice each and the feelie that was the target item was presented four times. The object presentation order within the 22 experimental trials of each block were randomized, controlling for any order effects. The experiment consisted of eight learning blocks. Block was a within-subjects repeated measure. Dependent variables in this study included the number of learning blocks taken for each participant to reach 100% accuracy, discrimination sensitivity (measured as d′) for each block (Macmillan & Kaplan, 1985), and response time for each trial (in milliseconds).

2.5 Procedures

The experiment was conducted online, with participants accessing the experiment on a personal computer with high-speed internet connection. Stimuli were displayed on a computer screen and participants responded using an input device (i.e., mouse, touchscreen, or keyboard). Moving stimuli rotated counterclockwise about a fixed vertical axis at a rate of approximately 3.75 rotations per minute (rpm). This resulted in objects rotating 67.5° during 3-second stimulus study presentations and 45° during 2-second test presentations.

The procedure used in this study was adapted from Gibson & Gibson's (1955) experiment with slight alterations: Use of fewer objects in the current study (10) compared to the original study (30), repeated presentations of non-target items (twice) in the current study, omission of re-presentation of target object at the end of each block, and shorter presentation times in the current study (3s for target study and 2s for test compared to 5s for study and 3s for test in the original Gibson experiment). Presentation times were reduced to discourage the use of cognitive strategies (e.g., memory cues and associates) by participants when learning to discriminate objects. Given the principle of the ecological theory of perceptual learning, attempting to minimize the involvement of cognitive processing was essential. Reduced presentation times, omission of re-presentation of target objects, and repeated presentations of non-targets were implemented to increase the difficulty of the task and avoid a possible ceiling effect.

Upon signing up for the study in SONA, participants were supplied a link to access the experiment website. First, participants were shown an informed consent document explaining the experiment and their rights. Participants who checked the informed consent box at the end then proceeded to the demographics and visual acuity screening questionnaire. Participants then progressed to a screen explaining the nature of the task and displaying instructions for responding. Participants were told they would periodically be presented with a target object (which was the same throughout the experiment) along with a series of several other objects (which looked similar to the target). Their task was to study the target object carefully (which was identified as such each time it was presented for study; i.e., labeled 'TARGET') and respond whether each presented object was identical to the target object ('same') or not identical to the target (‘different’) by selecting ‘same’ or ‘different’ from the multiple choice response list displayed after each test object presentation. Participants had 3 seconds to study target objects, 2 seconds to view each test objects, and unlimited time to respond. Participants in either of the motion conditions viewed objects as 3-second videos for target objects and 2-second videos for test object presentations. Participants in the static conditions viewed images of target and test objects for 3 and 2 seconds, respectively. No feedback was given on any trial.

At the start of each trial, before any object was presented, a fixation cross appeared in the middle of the screen for 500ms. This was immediately followed by a 250ms blank screen, after which the target or test object was shown. Once the viewing period had elapsed, a screen displaying the response options (‘Same,’ ‘Different’ and, in the case of an improperly displayed stimulus, ‘Error’) was shown. Participants selected their response and confirmed their choice by clicking the ‘Submit’ button to progress the experiment. After a response was made, a blank screen was displayed for 250ms followed immediately by a visual noise mask (black-and-white checkerboard) for 250ms to ensure that after-image effects on the next stimulus presentation are minimized, which subsequently began with another 250ms blank screen and a 500ms fixation cross presentation before displaying the next object (see Figure 2). Learning blocks proceeded until all 8 blocks were complete, at which time a screen displayed a message saying that the experiment was complete. Participants were given no feedback at any point in the experiment and were not aware of the 100% accuracy learning criterion but were told to focus on accuracy while still trying to respond quickly.

2.6 Results

2.6.1 Data Processing

2.6.1.1 Exclusion Criteria

Participants who did not complete the experiment were excluded from statistical analyses due to incomplete data.

2.6.1.2 Technical Difficulties

In the event that a stimulus was not properly displayed during presentation, participants were told to enter a response of ‘Error.’ To perform d-prime calculations, a response of ‘Same’ or ‘Different’ is required. Thus, the decision to code Error responses as False Alarms (in the case of non-targets) or Misses (for targets) was made to provide more conservative calculations of accuracy. Data from any participants whose data was composed of more than 25% missing or error responses (combined) was categorized as ‘incomplete’ and was not included in analyses.

2.6.1.3 Correction to d-prime

d-prime was calculated using corrected Hit and False Alarm values. In the event of total Hit or False Alarm values of 0 or 1, corrections were required to calculate d-prime. Rates of 1 were replaced with 1-(1/2n). False alarm rates of 0 were replaced with 1/2n, where n is the number of signal or noise trials (Macmillan & Kaplan, 1985; Wickens, 2001). Hit rates of 0 were replaced with .0001.

2.6.1.4 Response Time Outliers

Response times that were 3 standard deviations above the average response time were regarded as outliers and removed during data analysis. Trimming resulted in the removal of 0.5% of trials.

2.6.2 Data Analysis

2.6.2.1 Accuracy and Blocks to Criterion

A 2 View (side, top) x 2 Motion (rotation, static) between-subjects analysis of variance (ANOVA) was used to compare the mean number of learning blocks needed to reach 100% accuracy between the four possible conditions to test for potential effects of viewpoint, motion, and any interaction between the two variables. A linear mixed-effects model was used to analyze any potential differences in d-prime across blocks within each of the four conditions and to compare patterns of change in d-prime between conditions, with Subject being a random effect and all other variables being fixed effects. Data over blocks is typically analyzed across absolute block progression (from the first block to the last block needed to reach criterion), with all participants advancing through learning blocks until they reach the 100% learning criterion. However, because differences in learning rate between participants resulted in unequal numbers of completed learning blocks (some took more blocks to reach criterion, while others required fewer), this approach is not ideal for capturing improvements that result from the process of perceptual learning. Considering that learning in this study was demonstrated as increases in object discrimination accuracy (with the goal of achieving perfect accuracy), a more realistic representation of learning would follow changes in performance working backwards from this common goal of perfect accuracy. By starting at a point where performance is equivalent across participants and moving through subsequent blocks, learning can be observed as changes in accuracy across relative blocks. This approach still captures individual differences but provides a more ecologically valid representation by recognizing that the function of perceptual learning is to enhance perceptual abilities so that organisms can interact with their environment more efficiently. Relative blocks represent functionally equivalent stages of learning across individuals. The relative block on which the participant reached criterion was always labeled as Block 8. For example, if a participant reached criterion in Block 3, then the relative blocks corresponding to this participant assumed the values of 6, 7 and 8. If a participant finished in Block 5, then the relative blocks were labeled 4, 5, 6, 7, and 8, with 4 meaning the first block, and so on. Therefore, two mixed-effects models were used to examine learning. An absolute block model: d-prime ~ View * Motion * Block + (1 | Subject) and a relative block model: d-prime ~ View * Motion *newBlock + (1 | Subject), where newBlock is the factor that denotes relative blocks. Due to the fact that the value of the criterion was always equal to 3.046, the last block from each participant was omitted from the mixed model analysis since it would not add any useful variability to the statistical computation. The only exception to this rule was when a participant reached criterion on the first block, in which case the score was included in the analysis.

2.6.2.2 Survival Analysis

As mentioned previously, data from 60 participants who completed the experiment but failed to reach criterion were not included in previous analyses. However, using a Kaplan-Meier survival analysis (Kaplan & Meier, 1958), data from these participants was analyzed together with data from participants who successfully reached criterion to compare survival rates of conditions. “Survival” denotes the absence of an event occurring. In this study, the event was reaching the 100% accuracy learning criterion. Participants “survive” until they reach criterion, at which point they were removed since they no longer progressed through learning blocks. Participants who never experienced the event (i.e., never reached criterion) were categorized as ‘censored.’ Thus, survival analysis examined the pattern of learning using data from all participants who completed the study, not just those who reached criterion. Comparing the survival distributions of each condition made it possible to determine the influence of each independent variable on survival (i.e., learning). Two analyses were conducted, one to test the equality of survival distributions for the different levels of Motion (Moving vs. Static) and another to test the equality of survival distributions for the different levels of View (Side vs. Top). A cumulative survival rate of 1 indicates 100% of participants are still in the study (i.e., have not yet reached criterion). A cumulative survival rate of 0 indicates 0% of participants are still in the study (i.e., have reached criterion).

2.6.2.3 Response Time

Response time (RT) was defined as the time between the appearance of the response list on the computer screen and participants’ confirmation of a response by pressing the ‘Submit’ button. A linear mixed-effects model was used to analyze any potential differences in response times across learning blocks within each of the four conditions and to compare patterns of response time changes between conditions. Trial and Subject were random effects, such that Trials were embedded within Subjects, and all other variables were fixed effects: RT ~ View * Motion * NewBlock + Trial + (Trial | Subject).

2.6.3 Accuracy

The number of Hits (correctly responding that the target stimulus is present when it is present; H), Misses (incorrectly responding that the target stimulus is not present when it is present; M), Correct Rejections (correctly responding that the target stimulus is not present when it is not present; CR), and False Alarms (incorrectly responding that the target stimulus is present when it is not present; FA) were recorded for each learning block. Using the Hits, Misses, and False Alarms, a measure of discrimination (d-prime or d′; Macmillan & Kaplan, 1985) was calculated for each learning block. The number of learning blocks taken for each participant to reach the established learning criterion (100% accuracy; 4 H & 18 CR; 0 M & 0 FA) was also recorded. For the set of objects presented in blocks of trials the criterion value of d′ was 3.046.

When analyzed across absolute blocks, a mixed model revealed a significant main effect of Block ($\beta = .343$, $SE = .0815$, $p < .001$), demonstrating increases in d-prime over learning blocks. There was a significant main effect of Motion ($\beta = .985$, $SE = .3996$, $p < .02$), such that overall d-prime was higher when objects were presented statically. There was also a significant Motion x Block interaction ($\beta = -.331$, $SE = .1452$, $p < .05$), which was qualified by a significant View x Motion x Block interaction ($\beta = .457$, $SE = .2137$, $p < .03$), indicating that accuracy improved more quickly and showed a more stable pattern across blocks when objects were shown from the side while rotating (see Figure 3). A complete summary of these results is shown in Table 1. Effect sizes correspond to β values in Table 1, as unstandardized regression coefficients are the best estimates of the magnitude of effects in mixed models (see Pek & Flora, 2018). When analyzed across relative blocks, the same mixed model resulted in no significant effects.

2.6.4 Blocks to Criterion

A between-subjects factorial analysis of variance (ANOVA) was conducted using the average number of blocks taken to reach criterion in each condition. Results yielded a significant main effect of Motion (see Figure 4), indicating that participants reached criterion within fewer blocks in conditions where objects were presented statically compared to condition with motion, $F(1,171) = 31.864$, $p < .001$, $\eta 2p = .157$. This effect occurred regardless of viewpoint, demonstrating no significant interaction between View and Motion. There was no significant main effect of View ($F(1,171) = .003$, $p = .957$, $\eta 2p < .001$).

2.6.5 Survival Analysis

Log-rank comparisons of survival rates for moving versus static stimuli were significant for both the Topview condition ($\chi 2(1, N = 235) = 8.53$, $p = .004$) and the Sideview condition ($\chi 2(1, N = 235) = 15.86$, $p < .001$), demonstrating a main effect of Motion such that survival rates decreased more rapidly (i.e., participants reached criterion sooner) when stimuli were presented statically (see Figure 5). Log-rank tests found no significant difference in survival distributions based on Viewpoint, either with moving stimuli ($\chi 2(1, N = 235) = .08$, $p = .785$) or static stimuli ($\chi 2(1, N = 235) = .50$, $p = .479$).

2.6.6 Response Time

When analyzed across absolute blocks, a mixed model revealed only a significant main effect of Block ($\beta = -77.740$, $SE = 15.680$, $p < .001$), demonstrating decreasing response times over blocks. As previously mentioned, analysis across absolute blocks is arbitrary because individual differences in rates of learning lead to unequal comparisons across blocks. A more appropriate method is to express the data using relative blocks, so functionally equivalent stages of learning across participants are represented across blocks. Analysis over relative blocks revealed a significant main effect of NewBlock ($\beta = -80.871$, $SE = 15.569$, $p < .001$), indicating decreasing response times over block progression. There was also a significant Viewpoint x Motion interaction ($\beta = -666.225$, *SE* = 331.578, $p < .05$), which was qualified by a significant Viewpoint x Motion x NewBlock interaction, demonstrating that response times were fairly constant and stable over blocks across Movement conditions when objects were shown from a sideview (see first graph in Figure 6). However, when objects were shown from a top view, response times were initially quite different, with times in the motion condition being three times slower than in the static condition, before converging as participants approached criterion (see second graph in Figure 6).

2.7 Discussion

Experiment 1 provided partial support for Hypothesis 1 that perceptual learning should be faster and more accurate when there are opportunities to explore objects from multiple viewpoints. Learning improved more dramatically and showed a less variable pattern over absolute blocks when objects were shown from the side while in motion (significant View x Motion x Block interaction on d-prime). Although learning was generally slower (required more blocks) when objects were presented as moving, a more efficient pattern of learning was observed when objects were also shown from the side, and trial-by-trial response times in this condition were similar to the condition when objects were presented statically from the side. This suggests a speed-accuracy trade-off where participants required more practice (i.e., learning blocks) to reach criterion when discriminating moving objects, but also demonstrate consistent, high accuracy in their responses while taking a similar amount of time on each trial to those who experienced objects statically.

Interestingly, this improvement from multiple viewpoints only emerged when information was provided through both a side view and movement, but not from the individual contributions of each variable. The hypothesis that presentation from a side view would facilitate better learning was not supported when examining Viewpoint in isolation: accuracy, response times, and survivability were all similar in direct comparisons of a side view and a top view. The presence of rotation alone also did not benefit learning, in fact, learning occurred sooner when objects were viewed statically. Although this finding directly contrasts with my prediction, one possible explanation is that the information provided by movement was simply not necessary for the simple object shape discrimination task used.

The choice to utilize an underspecified task in Experiment 1 was made to examine the influence of Movement and View in a controlled manner. However, this type of task does not provide a very accurate representation of the context in which learning occurs in our everyday lives. Perceptual learning follows the same principle as perception and action, our behavior has functional relevance. According to Gibson (1979) perception is a process of directly detecting meanings for action and not a matter of assigning meaning to objects with certain physical properties. Thus, the motivation underlying learning to better discriminate and identify objects should be closely linked to the intention to use that object. The absence of functional relevance may explain the lack of significant results when using relative blocks for analysis.

To examine the full effects of learning based on relative blocks (as opposed to absolute blocks) and the true benefit of exploration (combination of moving stimulus seen from side view), a functional task is necessary. The use of a functional task was also essential to testing my second hypothesis, that perceptual learning should be faster and most accurate when the task involves thinking about potential uses as opposed to simple discrimination. Therefore, Experiment 2 was designed to test Hypothesis 2 and provide a more ecologically valid representation of the process of perceptual learning.

CHAPTER III – Experiment II: Perceptual Learning of Feelies in Functional Tasks

According to Gibson (1979) the primary goal of perception is to guide future actions. In this sense, perception is the act of detecting functional relationships between the observer and objects or parts of the environment that are relevant to satisfying a particular behavioral task demand. By definition, perception is a functional act. By extension, perceptual learning should also be defined by a particular behavioral function or skill that is being learned. I tested this idea by priming the target objects used in the first experiment with a particular affordance. I expected that providing an affordance prime would enhance perceptual learning as compared to the relatively underspecified task (shape discrimination) used in Experiment 1. To this end, participants in the Provided Affordance (PA) prime condition were presented a short video of a person cracking nuts using one of the feelies. Labelling has been shown to improve short-term memory retention (Hagen & Kingsley, 1968), but is not beneficial in perceptual learning tasks (De Rivera, 1959; Ellis et al., 1962; Pfafflin, 1960; Rasmussen & Archer, 1961). Therefore, a condition where participants provide two physical descriptors of the target object (Generated Semantic condition) was added to test the hypothesis that affordance priming would facilitate learning better than labelling via semantic primes because affordances provide functionally meaningful information.

Additionally, because affordances and semantic associates have both been demonstrated to produce reliable priming effects (Surber et al., 2023), a fair comparison between the two requires that both primes be equivalent regarding level of processing. With deeper levels of processing, stimuli are more attended to and fully analyzed, which leads to better encoding and retention (Craik & Tulving, 1975). Generating semantic primes facilitates deeper processing than being provided a single affordance prime by the experimenter. To address this, a third condition was added in which participants generated two possible uses (affordance primes) for the target object at the start of each block. This made it possible to compare affordance priming and semantic priming at a level of deep processing. It was hypothesized that affordance priming would result in faster learning than semantic priming because affordances are directly perceived and require no additional processing steps like semantic associates. Evidence from neuroscience is consistent with this prediction. Norman (2002) suggested that visual object recognition (a putatively semantic process served by the ventral visual pathway in the cortex) is relatively slower than planning of future actions (affordance processing served by the dorsal visual pathway in the cortex). This means that people detect how and for what purpose they can use an object before they can consciously recognize the object. Additionally, we expected that the condition in which the affordance label was given by the experimenter (Provided Affordance) would be inferior to both deep processing conditions because it operates on a shallower level of processing. This is similar to the generation effect in memory where simply reading words produces inferior performance compared to having participants generate words (Slamecka & Graf, 1978). It was expected that the context resulting in optimal learning would be in the condition where the participant is asked to think of at least two potential uses (Generated Affordance prime) of an object that is rotating and presented from the side viewpoint.

3.1 Participants

There was a total of 426 participants in Experiment 2. 255 participants were USM undergraduates who were at least 18 years old and had not participated in Experiment 1.

The remaining 171 participants were recruited from Prolific.co. Individuals who participated via Prolific were screened to closely match individuals from the USM student sample (i.e., age 18-31, U.S. resident, fluent in English, normal or corrected to normal eyesight). Prolific participants received an average of $8.00 as compensation for their time spent completing the experiment. Data from 97 participants was excluded due to incompleteness (did not complete the full experiment). 64 participants completed the study but failed to reach the learning criterion during that time. As in Experiment 1, data from these participants was not analyzed for accuracy and reaction time together with the 265 participants who successfully reached criterion but were included in survival analyses.

3.1.1 Demographics

Participants were primarily young adults (*M* = 22.51, *SD* = 4.74). The majority of participants identified as female (N = 215), with a smaller portion identifying as male (N = 103) or another gender (N = 11). Self-report data of participants' racial identities shows that most participants were White (N = 210), but the sample also included Black (N = 72), Asian (N = 26), American Indian (N = 3), and Other (N = 18) individuals.

3.2 Design

The experimental design and variables were identical to those used in Experiment 1 with the addition of Priming as an independent variable. Motion and Viewpoint remained between-subjects independent variables with two levels each. Priming was a between-subjects variable with three levels: Provided Affordance (PA); Generated Semantic (GS); Generated Affordance (GA). This resulted in a total of 12 conditions, to which participants were randomly assigned (Top-Motion-PA: n = 22; Top-Motion-GS: n

= 23; Top-Motion-GA: n = 23; Top-Static-PA: n = 22; Top-Static-GS: n = 22; Top-Static-GA: n = 22; Side-Motion-PA: n = 22; Side-Motion-GS: n = 22; Side-Motion-GA: n = 22; Side-Static-PA: n = 22; Side-Static-GS: n = 21; Side-Static-GA: n = 22)

3.3 Procedures

The general procedure was identical to Experiment 1 (same-different discrimination task, learning blocks of 23 trials, 3-second target presentations, 2-second presentations for test objects) with the important addition of the three priming conditions. In the Provided Affordance condition, once the target object was displayed for study at the start of each block, participants were shown the message: "Now imagine that the target object is being used to crack open nuts. Like so:" followed by a short soundless video in which the object is grabbed by the hand and is used to crack open a peanut (see Figure 7). These prompts were designed to serve as affordance primes that provide a behavioral context for perceptual learning. In the Generated Semantic condition, semantic priming was facilitated by having participants describe the target object in terms of its physical appearance using at least two words (e.g., round, smooth, grey) immediately after it was presented for study. Participants typed their responses into a text box on the screen. The Generated Affordance condition was similar to the Generated Semantic condition, but participants were asked to describe two possible uses for the target object using action words/verbs (affordances, e.g., throw, squeeze) instead of physical appearance. This condition served as an affordance prime by providing a behavioral context for learning similar to the Generated Semantic condition but can be directly compared to the Generated Semantic condition because both conditions required more effort or deeper processing (by having participants generate primes) than the Provided Affordance condition.

3.4 Results

3.4.1 Data Processing

All data processing procedures in Experiment 2 including exclusion criteria, outlier identification, and corrections to measures were identical to those used in Experiment 1.

3.4.2 Data Analysis

3.4.2.1 Accuracy and Blocks to Criterion

As in Experiment 1, accuracy was examined using absolute blocks (sequentially from Block 1 to Block 7) and relative blocks (with the block in which criterion was reached labeled as Block 8, and all previous blocks assigned values 7, 6, 5, etc. in reverse order). Thus, with the addition of the Prime variable, linear mixed-model analyses included a model using absolute blocks: $d' \sim \text{View x Motion x Prime x Block} + (1 \mid \text{Subject})$ and relative blocks: $d' \sim \text{View x Motion x Prime x newBlock} + (1 \mid \text{Subject})$. As in Experiment 1, the last block of the experiment was always excluded from analyses (unless it is the only block to analyze) due to a lack of variability.

Blocks to Criterion was used as a dependent measure in a 2 (View) x 2 (Motion) x 3 (Prime) between-subjects ANOVA analysis.

3.4.2.2 Survival Analysis

As in Experiment 1, data from participants who completed the experiment but failed to reach criterion were not included in analyses of accuracy and response time. However, data from these 64 participants was analyzed along with data from participants who successfully reached criterion using a Kaplan-Meier survival analysis method (Kaplan & Meier, 1958). Survival distributions of each condition were compared, including how motion, viewpoint, and priming affected patterns of learning. Because there was no main effect of View in the ANOVA on blocks needed to reach criterion and because viewpoint was shown to have no significant influence on survival rates in Experiment 1, survival rates were collapsed across viewpoints. The analysis compared survival distributions between moving and static stimuli within each of the three priming conditions.

3.4.2.3 Response Time

RT was analyzed using the same type of mixed model (employing the lmer function in R) as in Experiment 1 with the addition of Prime as a fixed factor: RT ~ View x Motion x Prime x Block + Trial + (Trial | Subject).

3.4.3 Accuracy

When analyzed across absolute blocks the mixed model using d′ as the dependent variable resulted in no significant effects. The same analysis over relative blocks (see Table 2) yielded a significant main effect of Motion ($\beta = -5.12$, $SE = 1.56$, $p < .001$), such that the average d′ for the Motion condition was smaller ($M = 1.79$, $SD = 0.96$) than the Static condition ($M = 2.04$, $SD = 0.82$). The Motion x Prime interaction was also significant when comparing the GS to the GA condition ($\beta = 6.21$, $SE = 2.01$, $p < .003$), and when comparing the PA to the GA condition ($\beta = 6.85$, $SE = 2.14$, $p < .002$), such that there were greater differences in average discriminability between static and moving stimuli in the GS and PA conditions than in the GA condition (see Figure 8).

There was a significant Motion x NewBlock interaction ($\beta = .77$, $SE = .18$, $p < .002$), wherein presenting rotating objects resulted in more stable increases in d′ over blocks compared to statically presented stimuli which varied more from one block to the next (see Figure 9).

The significant Motion x Prime x NewBlock interaction when comparing the GS and GA prime conditions ($\beta = -.85$, $SE = .31$, $p < .01$), and when comparing the PA and GA prime conditions ($\beta = -1.04$, $SE = .33$, $p < .01$) indicated that patterns of learning (changes in d′ over blocks) between rotating and static stimuli converged more quickly in the GS and PA conditions than in the GA condition, where motion facilitated a more accurate and more stable pattern compared to the static condition (see Figure 10).

The significant View x Motion x Prime interaction in the context of comparing the PA to the GA condition ($\beta = -6.75$, $SE = 2.81$, $p < .02$) was qualified by a significant View x Motion x Prime x NewBlock interaction ($\beta = 1.11$, $SE = .43$, $p < .02$), wherein the presence of motion produced a pattern of learning over blocks that was more stable and was overall closer to criterion from the start compared to the static condition, but only in the GA condition where objects were viewed from the side (see Figure 11). No other main effects or interactions were significant.

3.4.4 Blocks to Criterion

A between-subjects factorial ANOVA was conducted using the average number of blocks taken to reach criterion in each condition. There was a significant main effect of Motion, $F(1,253) = 8.45$, $p < .01$, $\eta^2_p = .032$, indicating that participants reached criterion in fewer blocks in conditions where objects were presented statically compared to the condition in which the stimulus was rotating. No other main effects or interactions were significant.

3.4.5 Survival Analysis

The results of a log-rank test found that survival rates between motion and static condition were only significantly different in the GA condition, where learning was slower in the motion condition than the static condition, $\chi 2(1, N = 329) = 8.25$, $p = .004$ (see top panel in Figure 12). In the GS and PA prime conditions survival rates were not significantly different between static and rotating stimuli. Viewpoint did not have an impact in any of the prime conditions on survival rates.

3.4.6 Response Time

The main effect of Prime was significant. Specifically, RT was faster in the GA prime condition (M = 2311.1ms, SD = 691.9ms) than in the PA prime condition (M = 2274.6ms, SD = 665ms), $\beta = -404.8$, $SE = 193.1$, $p < .04$. The comparison between the GS (M = 2396.2ms, SD = 989ms) and PA prime was also significant ($p<.05$). This was qualified by several higher order effects. Motion x Prime was significant via the comparison between PA and GA prime conditions, $\beta = 703.96$, $SE = 291.2$, $p < .02$. This was further qualified by the View x Motion x Prime interaction via the comparison between the GS and GA primes, $\beta = 848.1$, $SE = 414.2$, $p < .05$. The Motion x Prime x Block interaction varied over absolute blocks in two ways: 1) between GS and GA (β = 217.6, $SE = 90.7$, $p < .02$), and 2) between PA and GA ($\beta = -220.4$, $SE = 93.4$, $p < .02$). Finally, analysis over absolute blocks yielded a significant View x Motion x Prime x Block interaction ($\beta = 254.20$, $SE = 125.58$, $p < .05$), indicating that average response times over blocks were shorter in the motion condition compared to the static condition and this varied by view and between primes (see Figure 13). As previously noted, analysis across absolute blocks is arbitrary because it fails to adequately capture functionally equivalent stages of learning due to individual differences in the number of blocks taken to reach criterion. Some participants reach criterion in fewer blocks than others and, consequently, are not included in averages of subsequent blocks. Therefore, I have chosen to focus on the results of the mixed model that utilized relative, rather than absolute, blocks.

Analysis over relative blocks resulted in no significant main effects. There was a significant Motion x Prime interaction carried by the comparison between the PA and GA prime conditions, $\beta = 1742.13$, $SE = 759.24$, $p < .03$; a significant View x Motion x Prime interaction, also carried by differences between the PA versus GA primes, $\beta = -2156.41$, $SE = 1024.81$, $p < .04$; a significant Motion x Prime x NewBlock interaction carried by differences between the PA and GA primes, $\beta = -227.50$, $SE = 97.76$, $p < .02$). All these interactions were qualified by a significant View x Motion x Prime x NewBlock interaction in the context of differences between the PA and GA primes, $\beta = 289.64$, $SE = 131.34$, $p < .03$. This four-way interaction demonstrated that differences in response times between static and motion conditions were greatest at the beginning of the study, with responses generally being faster in conditions where motion was present. Response times converged as participants approached criterion, with this convergence being most pronounced in the GA prime condition when objects were shown from the side. Although response times converged in all priming conditions and in both View conditions, the patterns of response times in the GA Sideview condition became remarkably consistent very quickly (see first graph panel in Figure 14).

3.5 Discussion

In Experiment 2, I hypothesized that perceptual learning would be faster and most accurate when paired with a task that involves thinking about potential uses as opposed to simple discrimination, because perceptual learning (similar to perception) is best defined by actionable uses, i.e., affordances (H2). More specifically, I hypothesized that viewing a rotating object (H1A) from a side view (H1B) while actively thinking about what it can be used for (H2) should be the optimal combination of factors leading to fastest and most accurate learning because this circumstance would portray objects in a manner that most closely represents how we encounter objects in the real world: in motion, from a slightly angled side view, with the intention to utilize observed objects in a meaningful way.

The results of d′ analyses over absolute blocks did not support Hypothesis 2. There were no significant effects on accuracy (d′), and analysis over average response times by absolute blocks was functionally arbitrary because comparisons between participants are not equivalent across blocks. The lack of significant results using absolute blocks was consistent with Hypothesis 2. As discussed previously, a functional task is necessary to examine the full effects of learning based on exploration (Motion and View) on perceptual learning. Unequal comparisons over absolute blocks would likely not be able to detect any effects that emerged within a more functional task. Given that the addition of priming conditions led to a more functional task in Experiment 2 compared to Experiment 1, this outcome is not surprising especially when considering the results yielded from analysis over relative blocks.

Analysis over relative blocks provided support for Hypothesis 2 in several ways. The significant interaction between movement and priming demonstrated more consistent accuracy between static and moving stimuli in the most functional (Generated Affordance) condition. This similarity in accuracy persisted despite participants requiring more blocks to reach criterion in the GA condition, as indicated by the results of the survival analysis and the ANOVA on blocks to criterion. Furthermore, the presence of motion produced a steeper and more stable learning pattern over relative blocks compared to the static condition, but this only occurred when participants engaged in the most functional task, actively generating possible uses for target objects. Motion provided some benefit to learning compared to static presentation, as evidenced by less variable increases in d-prime over relative blocks compared to static presentation. However, the influence from motion was only able to fully emerge in the context of a functional task. Additionally, the benefit of motion (compared to static) in the same functional task was most pronounced when objects were shown from the side, which was designed to resemble the viewing angle we are most likely to encounter objects in our everyday lives. The cumulative effect of motion, side view, and affordance priming on perceptual learning supports the hypothesis that a combination of motion and a side view would lead to improved learning due to active sampling through exploration (Hypothesis 1) and that these factors would become most beneficial when paired with a task that required participants to perform active generation of potential uses of objects because perceptual learning is functional in nature (Hypothesis 2).

The convergence of response time patterns across viewpoints, movement, and primes also supports Hypothesis 2. Although initially there were larger differences between response times for moving and static stimuli, these differences dissipated as participants neared the end of the experiment. This convergence was particularly quick and consistent when participants performed the most functional priming task (GA) and viewed rotating objects from the side. This underscores the finding that information from active sampling through rotation, and a side view can most effectively be utilized when applied to a functional task.

The addition of functional tasks in Experiment 2 also permitted better examination of the influence of movement and viewpoint on perceptual learning, specifically, how the active sampling provided by motion and seeing objects from a side view should produce the most effective pattern of learning (Hypothesis 1). The hypothesis that motion would lead to better learning (H1A) was not supported by the finding that criterion was reached sooner (fewer blocks) when objects were presented statically. However, averaging performance over conditions fails to capture changes in accuracy over blocks. Given that learning is a gradual process of change, this result is not as meaningful as one from an analysis that examines performance as changes over learning blocks. When analyzed over relative blocks, I did find support for better performance from motion. Presenting stimuli as moving produced more stable increases in performance over blocks compared to static presentation. Active sampling of a rotating stimulus resulting from presentation from the side (as opposed to the top) was also expected to improve learning (H1B). This was supported by the finding that while motion was beneficial in a functional task (GA condition), it provided the greatest benefit when combined with exposure to multiple viewpoints. (i.e., when objects were viewed from the side).

CHAPTER IV – General Discussion

The current study examined the nature of visual perceptual learning and factors that may influence it using ecologically valid, novel objects known as "feelies." Participants performed a same-different discrimination task over learning blocks until they could discriminate a target object (one of the feelies) from all other objects (the nine other feelies) without making any mistakes. This study took inspiration from an influential Gibson and Gibson (1955) study on perceptual learning of scribbles, but with the goal of investigating perceptual learning using more ecologically valid objects and functional tasks.

Learning occurred in all viewing conditions, as evidenced by increases in d′ over learning blocks and shorter response times across blocks. I hypothesized that perceptual learning would be faster and more accurate when there are opportunities to explore objects from multiple viewpoints (H1). This hypothesis was tested in two ways: by having the stimulus either move or be static, and by viewing the stimulus from the side or from the top. Specifically, it was predicted that perceptual learning should be faster and more accurate when the stimulus is viewed from the side as opposed to from the top, and when the stimulus is rotating around a vertical axis as opposed to being static. The results supported Hypothesis 1. Learning improved more quickly and showed a less variable pattern of accuracy over blocks when objects were shown from the side with motion, and although learning was generally slower when objects were presented as moving, the pattern of response times over the course of learning produced by moving objects shown from the side was the most consistent. Remarkably, improved performance only resulted from the interaction between both sources of viewpoint information. The presence of motion alone did not benefit learning, in fact, learning occurred sooner when objects were viewed statically, and there was no effect of viewpoint on performance. One possible explanation for the seemingly contradictory results of movement is that the information provided by movement was simply not necessary for the simple object shape discrimination task. Overall, these findings were consistent with previous research that motion is beneficial to visual perception of 3D shape (Norman, Bartholomew et al., 2008; Norman et al., 2000, Norman & Raines, 2002, Norman et al., 1995) but not always optimally utilized (Todd, 2004; Todd & Norman, 2003), and that presentation of multiple viewpoints (i.e., perspectives) is a rich source of information for visual perception by revealing multiple surface regions of objects that contain information about unique depths and orientations of visible surface points (Hayward, 2003; Todd, 2004).

I also hypothesized that perceptual learning would be faster and more accurate when the task involves thinking about potential uses as opposed to simple discrimination without a meaningful behavioral task at hand (H2). Specifically, perceptual learning should be the fastest and most accurate when participants are required to think of potential uses for the objects as opposed to when they are primed to think about a specific use provided by the experimenter, or when they are simply asked to describe the object's physical appearance. Combining this with Hypothesis 1 leads to the conclusion that viewing a rotating object from a side view while actively thinking about what it can be used for should be the optimal combination of factors leading to fastest and most accurate learning. I found support for this hypothesis, the most efficient and stable pattern of learning over blocks was produced when participants actively generated uses for moving objects that were shown from the side. Response times over blocks also converged most quickly in this condition, demonstrating that the information provided by the culmination of these variables was able to be detected and utilized effectively by participants to inform their perceptions and decisions.

In summary, participants learned to perfectly discriminate novel objects through repeated exposure to available information despite receiving no feedback during the experiment. The presence of motion and a side view perspective were expected to improve learning. Although each source of information did not benefit learning individually, the combination of moving stimuli shown from a side view produced a patten of learning that demonstrated consistently high accuracy in regard to shape discrimination. This synergistic effect was even more pronounced in the context of a functionally relevant task (i.e., generating potential uses for target stimuli). Response times indicated that participants' trial-by-trial response rates were similar in all conditions, with response times being slower at the start of the study and decreasing as participants approached criterion. Responses were initially slower in conditions with motion, but response times converged with those in the static conditions as accuracy improved, suggesting greater efficiency utilizing information provided by movement.

The advantage to learning observed with the moving stimuli viewed from the side could potentially be attributed to this condition providing the greatest exposure of object surface area compared to other conditions. Compared to a static image, motion provides more information by uncovering multiple views of an object's surface as it rotates. When an object is shown from a side view perspective, previously occluded surface points become visible through rotation, so each new display is unique and reveals more of an object's 3D shape. However, from a top view perspective, the surfaces on an object's sides and bottom are occluded and never revealed by rotation about a vertical axis (as used in this study). Thus, it is possible that the nature of the benefit from motion and a side view is the result of more total surface information being available in that condition compared to other conditions. Future studies should investigate this possibility by quantifying and controlling the amount of exposed visible surface area of objects during perceptual learning tasks.

Despite this alternative interpretation, the findings of this study support the conclusion that perceptual learning requires active sampling through exploration, but a functionally meaningful task (i.e., affordance) is necessary to create the appropriate circumstance to most effectively utilize these sources of information. Furthermore, the influence of these factors can only be revealed when data is expressed using relative blocks (that represent functionally equivalent stages of learning across participants) rather than absolute blocks.

4.1 Perceptual Constancy

For traditional theories of visual perception, the fact that objects project a multitude of different images on the retina depending on the egocentric viewpoints the observer occupies, or due to the motion of the stimulus (rotation, translation, partial occlusion, etc.) poses an insurmountable problem: how can the brain identify the same object from multiple retinal images that contain very different light patterns? The current study demonstrated that it is possible to identify the same object from multiple viewpoints and during rotations which effectively show multiple facets of the same object to the naked eye. How do we detect the same information across these very different retinal images? Gibson’s (1966) solution is simple: The information is invariant across multiple views and is available in many samples during continuous visual exploratory activity. The invariant pattern is discoverable by the sheer power of being exposed to rich information in every successive sample. Perceptual constancy is not a problem for the visual system if we assume that perception is not based on a two-dimensional projection of the stimulus on the retina. Instead, ecological approaches assume that perception (and by extension, perceptual learning) is a matter of active sampling of the ambient energy arrays and detecting invariant patterns of information that remain the same across viewpoints and motion. Some configurations (e.g., side view) are more useful and provide easier access to information that specifies an object, especially if the object is viewed with a particular use in mind.

4.2 Applications

These findings could prove useful in educational settings and situations involving training skillful behaviors, such as sports, medical diagnostics, and military maneuvers. For example, improvements in anticipatory ability and precise timing of attention have been linked to better performance in sports such as soccer, basketball, tennis, badminton, and darts. Research indicates that, through perceptual learning (via training), athletes acquire greater expertise in identifying important sources of information as well as determining the moment at which that information becomes available and most useful (Abernathy et al., 1999; Hagemann et al., 2006; Oudejans et al., 2005; Savelsbergh et al., 2010; Smeeton et al., 2005; Vickers et al., 2000). Like athletes, those in the military often experience situations that require advanced situational awareness and the ability to make fast, accurate decisions. Several researchers have investigated how we can best train these types of skills (Endsley & Robertson, 2000; Klein, 1997). These military trainings tend to be more cognitively focused than perceptual. Skills that benefit from perceptual learning training in sports could potentially generalize to a related domain (i.e., military). Therefore, more research into perceptual learning is needed in this area. Finally, perceptual learning can be used to improve the speed and accuracy with which medical professionals make certain diagnoses, such as screening for melanomas on patient's skin (Guégan et al., 2021) and detecting lung tumors on chest radiographs (Sha et al., 2020). Ultimately, understanding factors that influence perceptual learning could inform the development of training plans and strategies that produce stable patterns of perceptual learning more quickly.

4.3 Limitations

The current study was conducted online. This limits experimental control and generalizability but also resulted in considerable loss of data from technical difficulties and a higher rate of attrition than is typically encountered in lab studies. This study also used a limited sample, as most participants were younger adults (mean age of approximately 22) and were primary white females. Consequently, the generalizability of findings from this study may be limited.

Future studies that could advance this research include exploring perceptual learning of other objects that vary in complexity and shape, conducting future studies in a controlled, laboratory setting (as opposed to online), expanding the scope of perceptual learning to include other perceptual modalities, such as haptics, and including populations beyond younger adults, such as older and middle adults, and patient populations (e.g., the visually impaired, stroke victims, individuals with Parkinson's disease).

4.4 Connections Between Perceptual Learning and Motor Learning

In all the above-mentioned contexts the crucial component that was hypothesized to drive learning has been active exploration (Hacques et al., 2021). Active exploration enables the discovery of information that specifies future actions, and actions subsequently provide more opportunities for additional exploration. Information can be acquired from active exploration through performatory actions (such as using a tool) or exploratory activity, which involves actively seeking out information that specifies the properties and affordances of an event, object, or layout (Gibson, 1962; 1963; 1979). Although regarded as separate processes, the two operate in conjunction to inform the perception-action cycle. Organisms act to perceive just as they perceive to act, all so that they may be better suited to perform goal-oriented actions within their environment. Acquisition of skillful behaviors often involves a degree of motor learning as well. Everything from playing sports to walking on sloped surfaces requires careful coordination of movement. Emphasis is typically placed on the motor aspect of these behaviors, given the intrinsic connection between perception and action. Therefore, it is reasonable to assume that perceptual learning also plays a role in the development of these skills, and nowhere are perceptual and motor learning more connected than through haptics. Through haptics, we explore and perceive by movements of the hands, fingers, arms, body while being in direct physical contact with objects. Haptics involves the use of a variety of exploratory procedures (EPs), which are stereotyped movement patterns that possess certain characteristics that are invariant and are often highly typical (Lederman & Klatzky, 1987). EPs can be used to reliably detect information about various properties of objects. For example, one type of EP (lateral motion) presents as sideways movement between the skin and the surface of an object (i.e., rubbing), and is most often used to detect information about texture. Depending on the nature of the information being sought, different EPs are employed to achieve optimal (i.e., most accurate or efficient) haptic perception. Compared to vision alone, haptics offers the chance to investigate the role of motor learning in skill development and the opportunity to compare the involvement of perceptual learning and motor learning on development of skilled actions. Therefore, haptic perceptual learning stands out as a particularly worthwhile direction for future research that complements visual perceptual learning. Future research should reveal whether perceptual and motor learning are subject to some of the same influences that facilitate the maintenance of perceptual constancy not just for the sake of identifying and discriminating among objects, but also in the context of goal-directed, intentional behaviors that are accomplished by learning and perceiving specific uses (affordances) for objects.

4.5 Conclusion

The current study demonstrated that perceptual learning is an active process requiring exploration and a functionally meaningful task to create the optimal context for utilizing available information most effectively. These findings have implications for informing educational and training practices in various settings ranging from academics to sports, medicine, and military operations. Additional research is needed to further explore factors that influence perceptual learning and improve the generalizability of the current findings.

APPENDIX A – Tables

Table A.1 *Statistical output of the mixed model using the lmer function in R*

	β	*SE*	df	*t*	*p*
Intercept	0.487	0.278	350.80	1.754	0.0804
View (Top)	0.095	0.391	342.57	0.244	0.8076
Motion (Absent)	**0.985**	**0.400**	**380.86**	**2.465**	**0.0141***
Block	**0.343**	**0.082**	**335.07**	**4.209**	**<0.001*****
View (Top) x Motion (Absent)	-0.903	0.575	381.53	-1.57	0.1169
View (Top) x Block	-0.015	0.113	339.06	-0.14	0.8925
Motion (Absent) x Block	**-0.33**	**0.145**	**378.59**	**-2.278**	**0.0233***
View (Top) x Motion (Absent) x Block	**0.456**	**0.214**	**381.59**	**2.136**	**0.0333***
Significance codes: ***<0.001; **<0.01; *<0.05					

The effects in bold font are statistically significant.

Table A.2 *The mixed model with d' as the dependent variable across relative blocks*

	β	*SE*	df	*t*	*p*
Intercept	0.619	0.759	579.01	0.815	0.4153
View (Top)	-.715	0.968	580.77	-0.738	0.4606
Motion (Absent)	**-5.119**	**1.563**	**582.00**	**-3.276**	**0.0011****
Prime (GS)	-1.936	1.166	582.00	-1.661	0.0973
Prime (PA)	-1.167	1.101	574.77	-1.060	0.2895
NewBlock	0.147	0.119	545.24	1.234	0.2179
View (Top) x Motion (Absent)	3.014	2.038	581.83	1.479	0.1396
View (Top) x Prime (GS)	1.394	1.759	580.97	0.792	0.4286
View (Top) x Prime (PA)	0.308	1.482	578.440	0.208	0.83543
Motion (Absent) x Prime (GS)	**6.208**	**2.016**	**581.7**	**3.080**	**0.0022****
Motion (Absent) x Prime (PA)	**6.846**	**2.137**	**581.97**	**3.204**	**0.0014****
View (Top) x NewBlock	0.135	0.154	527.84	0.879	0.3800
Motion (Absent) x NewBlock	**0.768**	**0.238**	**561.17**	**3.223**	**0.0013****
Prime (GS) x NewBlock	0.235	0.183	538.00	1.288	0.1982
Prime (PA) x NewBlock	0.234	0.170	555.58	1.375	0.1697
View (Top) x Motion (Absent) x Prime (GS)	-5.395	2.944	579.33	-1.833	0.0674
View (Top) x Motion (Absent) x Prime (PA)	**-6.749**	**2.812**	**581.88**	**-2.401**	**0.0167****
View (Top) x Motion (Absent) x NewBlock	-0.464	0.312	560.97	-1.489	0.1371
View (Top) x Prime (GS) x NewBlock	-0.123	0.271	555.58	-0.453	0.6504

Table A.2 (continued).

	β	*SE*	df	*t*	*p*
View (Top) x Prime (PA) x NewBlock	-0.160	0.2317	545.2812	-0.692	0.48935
Motion (Absent) x Prime (GS) x NewBlock	**-0.853**	**0.3084**	**559.3996**	**-2.765**	**0.00588****
Motion (Absent) x Prime (PA) x NewBlock	**-1.039**	**0.3270**	**558.2321**	**-3.176**	**0.00158****
View (Top) x Motion (Absent) x Prime (GS) x NewBlock	0.729	0.4455 4	569.6433	1.636	0.10231
View (Top) x Motion (Absent) x Prime (PA) x NewBlock	**1.113**	**0.4311**	**558.6274**	**2.581**	**0.01011***
Intercept	0.487	0.278	350.80	1.754	0.0804
View (Top)	0.095	0.391	342.57	0.244	0.8076
Motion (Absent)	**0.985**	**0.400**	**380.86**	**2.465**	**0.0141***
Block	**0.343**	**0.082**	**335.07**	**4.209**	**<0.001*****
View (Top) x Motion (Absent)	-0.903	0.575	381.53	-1.57	0.1169
View (Top) x Block	-0.015	0.113	339.06	-0.14	0.8925
Motion (Absent) x Block	**-0.33**	**0.145**	**378.59**	**-2.278**	**0.0233***
View (Top) x Motion (Absent) x Block	**0.456**	**0.214**	**381.59**	**2.136**	**0.0333***
Significance codes: **<0.01; *<0.05					

Effects in bold font are statistically significant.

APPENDIX B – Figures

Figure B.1 *Three-Dimensional-Printed Versions of the Original 10 Feelies.*

All feelies were a homogenous dark gray and were topologically similar.

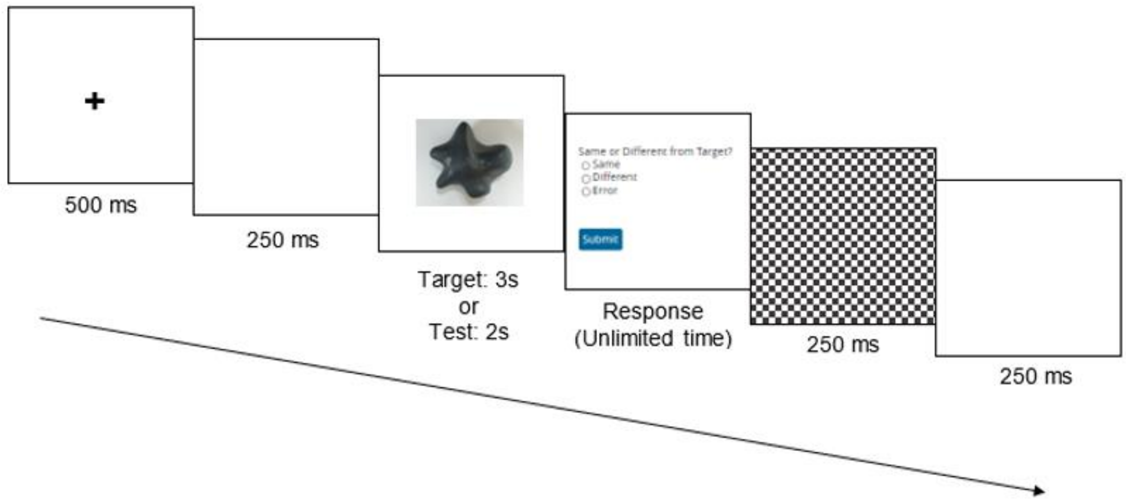

Figure B.2 *General Trial Sequence.*

Participants were presented with a target object to study, followed by several test objects for comparison, with the task of determining if each object is the same as or different than the target.

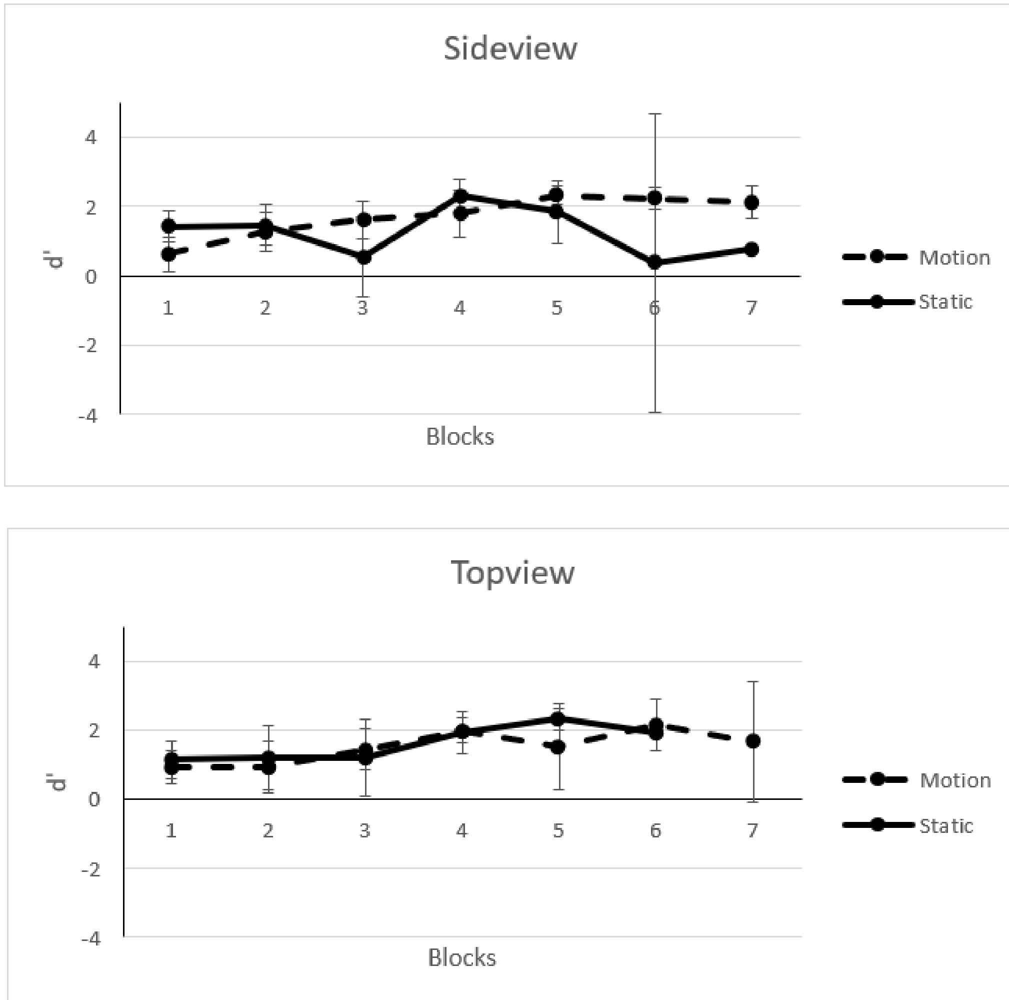

Figure B.3 *d' as a function of Motion and Viewpoint across absolute blocks.*

Error bars indicate 95% confidence intervals.

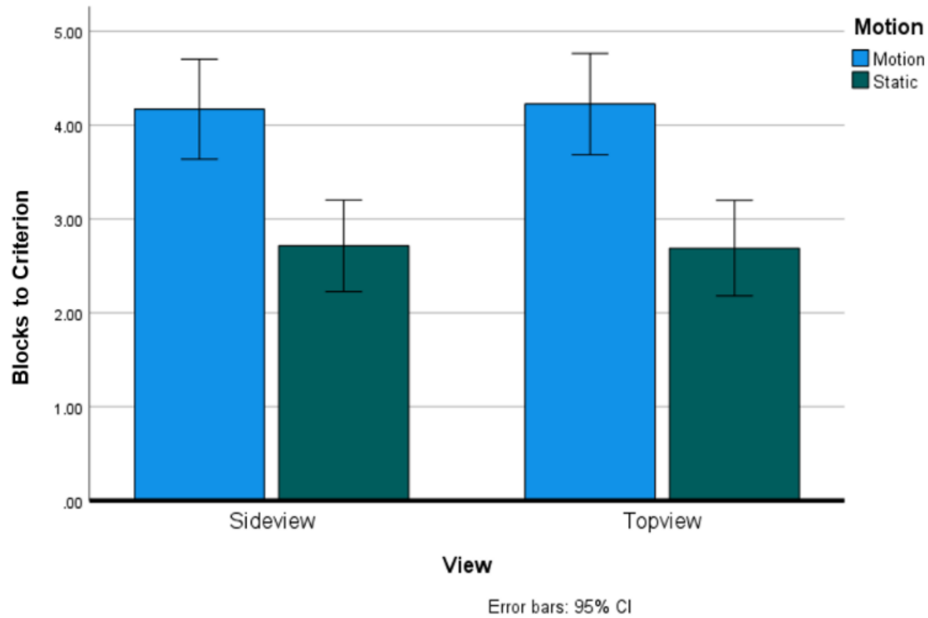

Figure B.4 *d' as a function of Motion and Viewpoint across absolute blocks.*

Error bars indicate 95% confidence intervals.

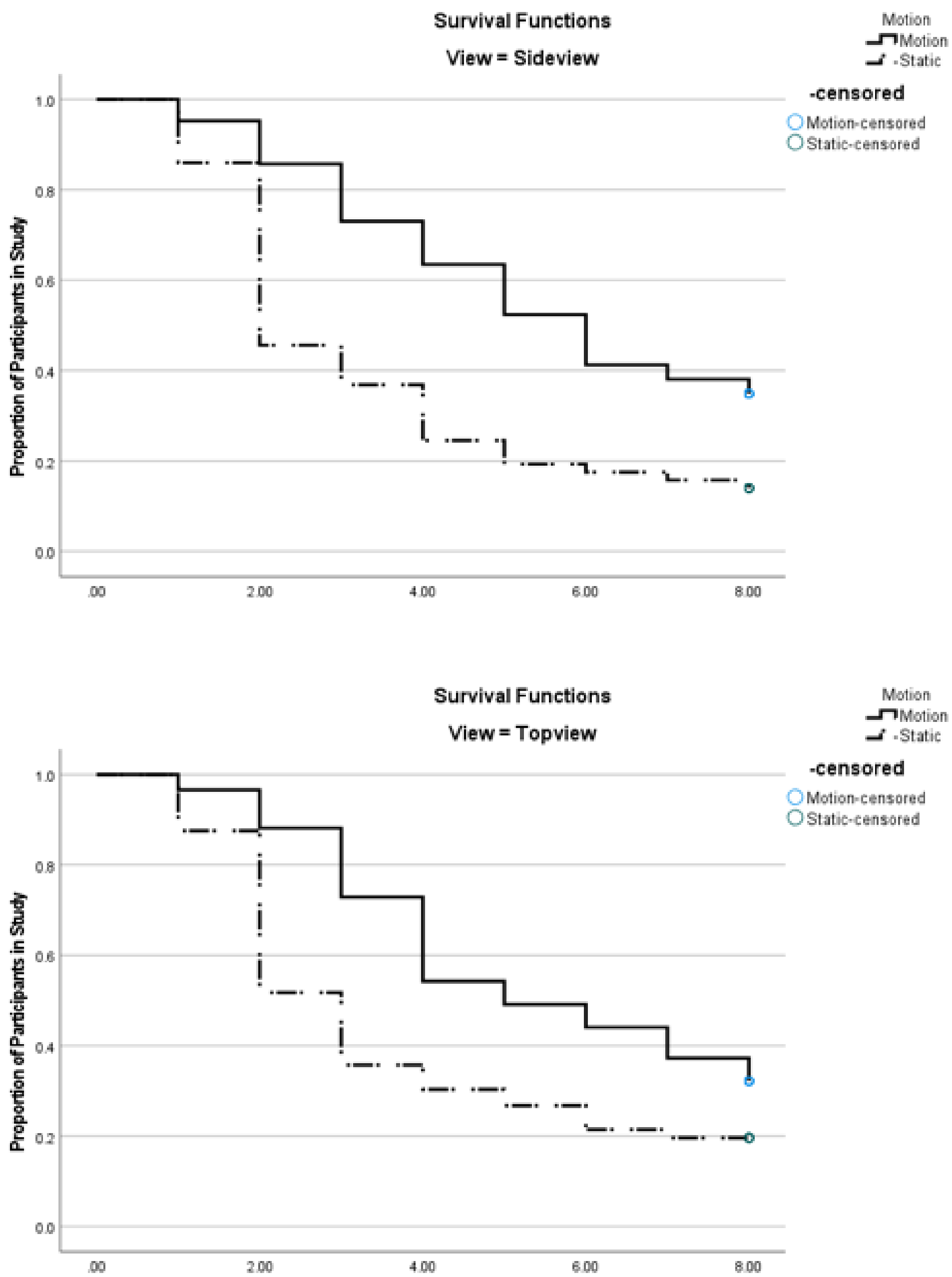

Figure B.5 *The rate of learning for rotating (full line) and static (dashed line) stimuli split by Viewpoint.*

Proportion of participants who did not reach criterion (i.e., did not achieve 100% accuracy) by Block 8 are indicated by the circle markers.

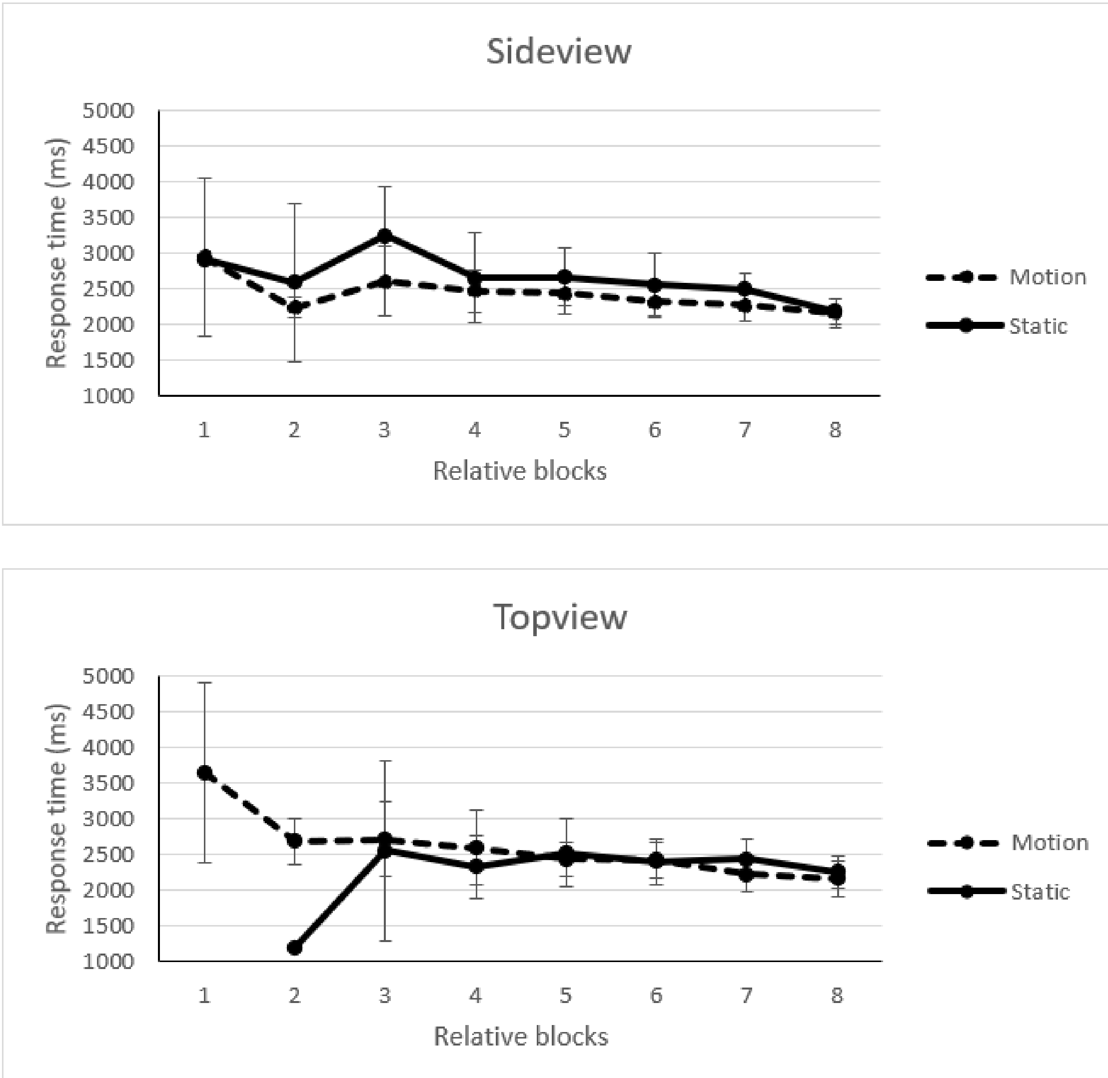

Figure B.6 *Response times as a function of Motion and Viewpoint over relative blocks.* Response time differences in learning occurred at the start of the experiment and converged at the end of the learning process, especially in the Topview condition. Error bars indicate 95% confidence intervals.

Generated Affordance: "*Describe two possible uses for the target object using action words (verbs)*"

Generated Semantic: "*Describe the target object's appearance using two words*"

Provided Affordance: "*Now imagine that the target object is being used to crack open nuts. Like so:* "

Figure B.7 *Instructions to Participants in the Priming Conditions.*

In the Provided Affordance condition participants were shown a video of the target object being used to crack open a peanut, as shown in the above still frame image.

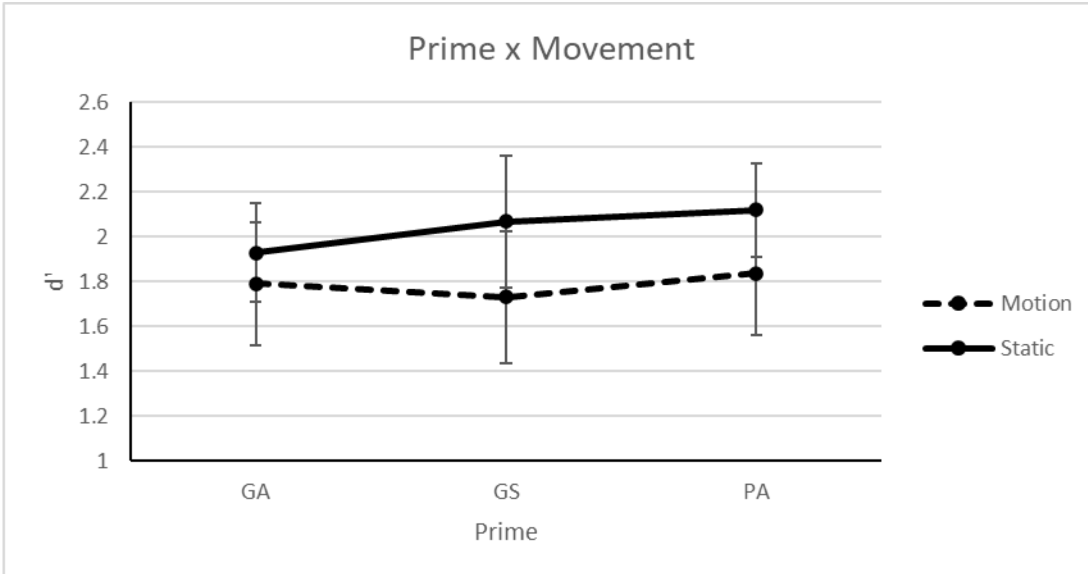

Figure B.8 *d' as a function of Prime and Motion.*

The significant interaction is carried by differences between GA and GS, and GA and PA primes, respectively. Error bars indicate 95% confidence intervals.

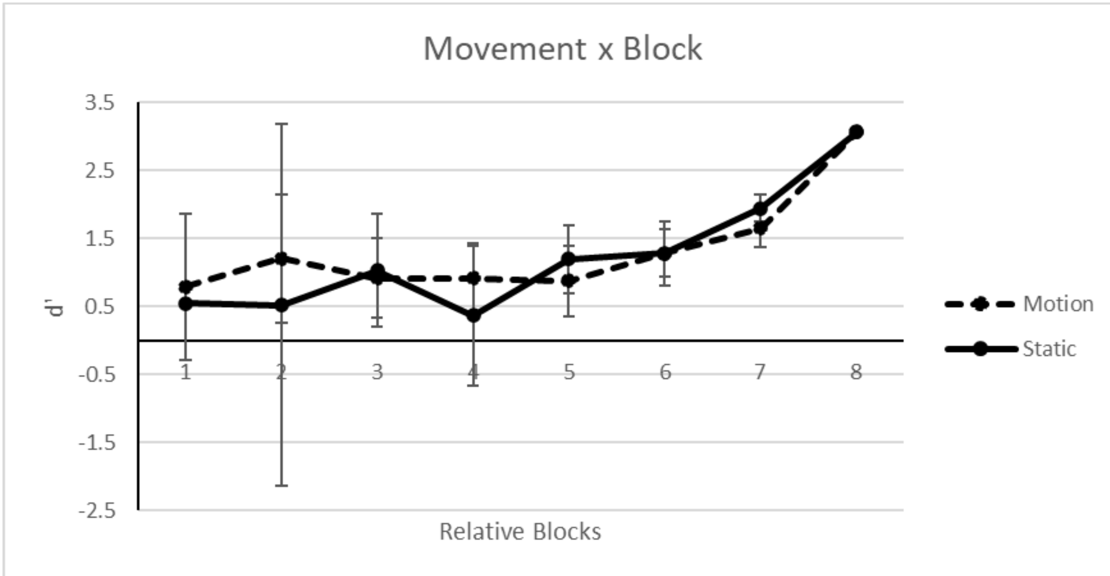

Figure B.9 *d' as a function of Motion versus Static stimuli across relative blocks.*

Error bars indicate 95% confidence intervals.

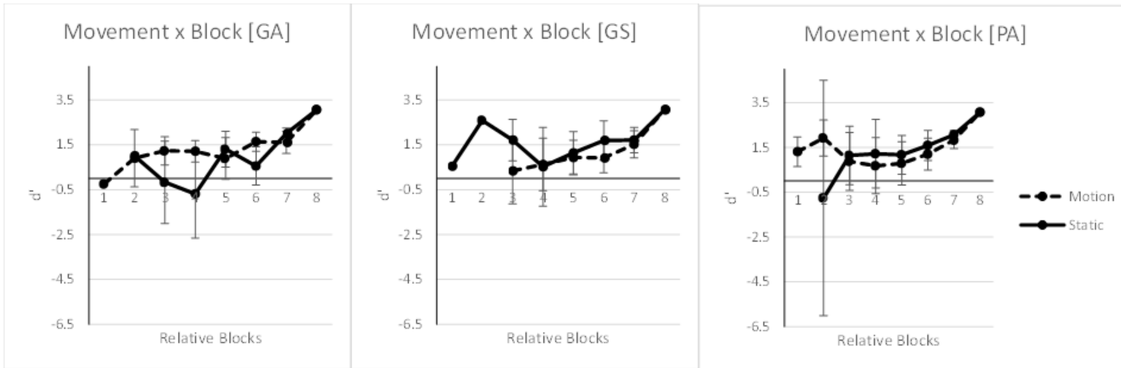

Figure B.10 *d′ as a function of Prime and Motion conditions across relative blocks.*

Error bars indicate 95% confidence intervals.

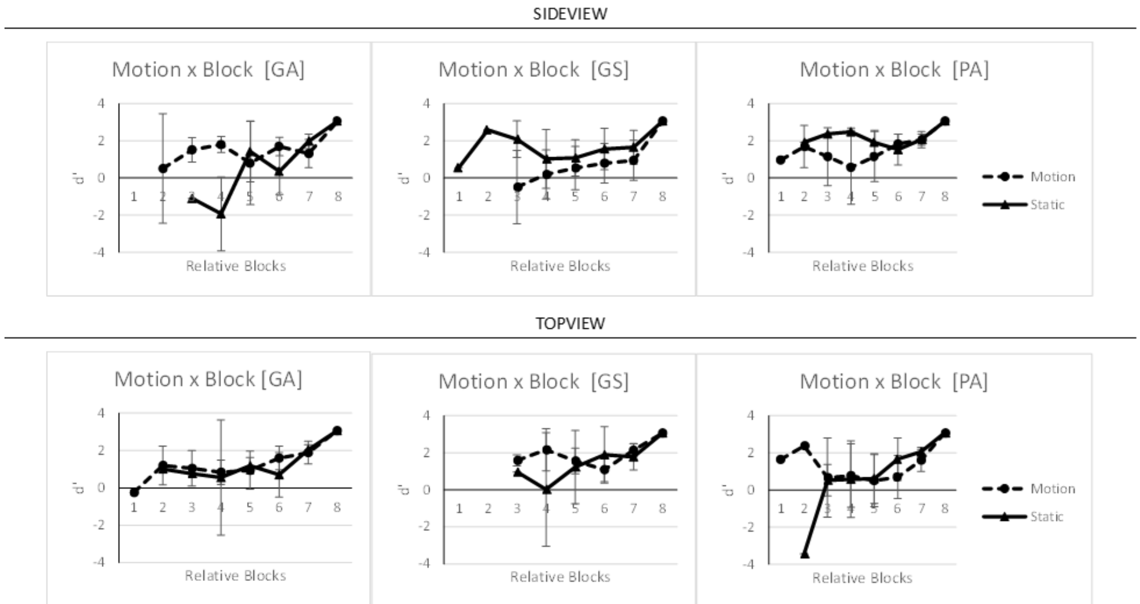

Figure B.11 *The View x Motion x Prime x NewBlock interaction.*

As predicted, rotating stimuli facilitated optimal learning when presented from the side after being exposed to the GA prime. Error bars indicate 95% confidence intervals.

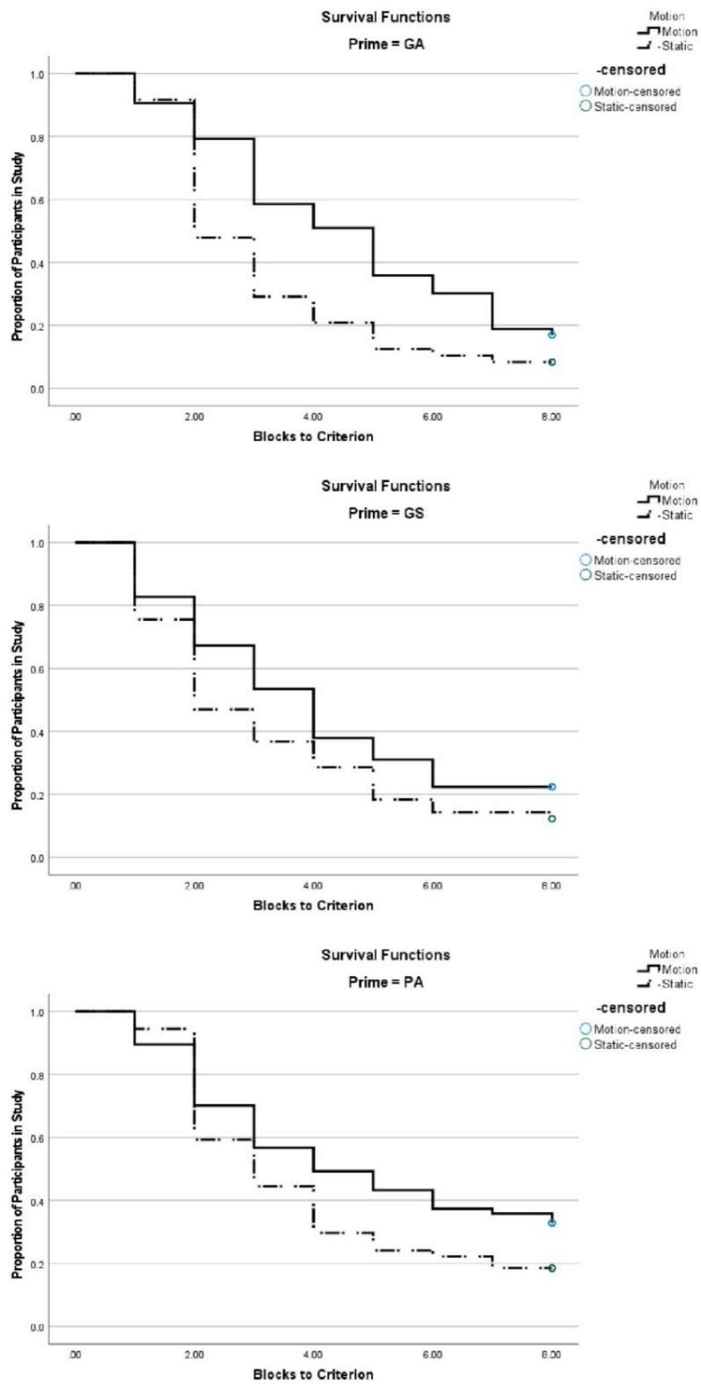

Figure B.12 *The rate of learning for rotating (full line) and static (dashed line) stimuli split by Prime type.*

Proportion of participants who did not reach criterion (i.e., did not achieve 100% accuracy) by Block 8 are indicated by the circle markers.

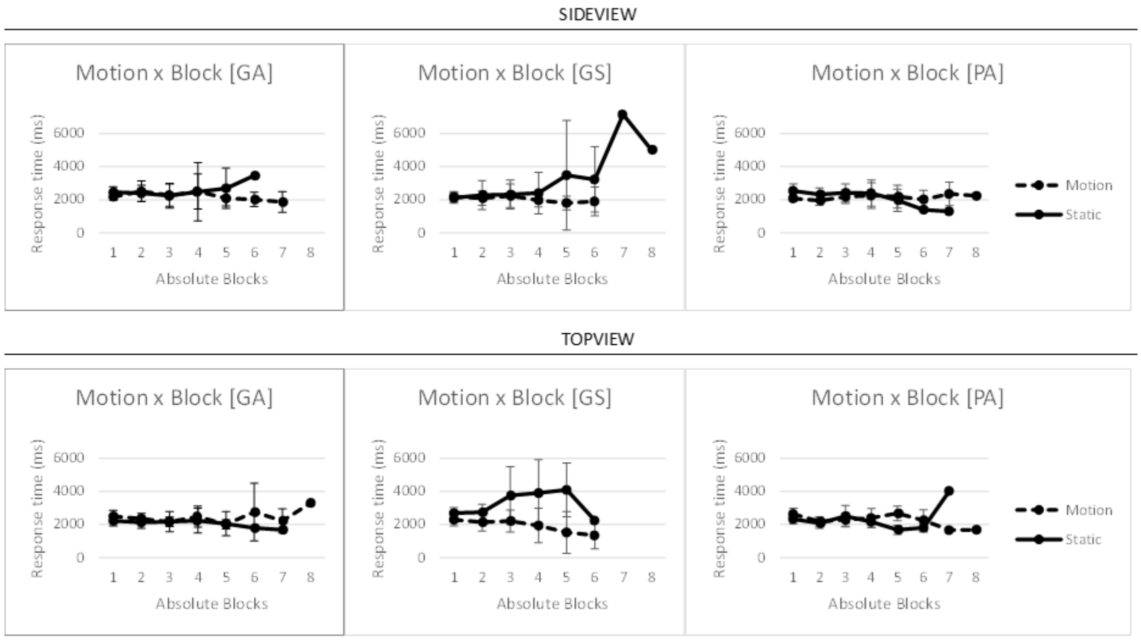

Figure B.13 *The View x Motion x Prime x Block interaction over absolute blocks on response time.*

Error bars indicate 95% confidence intervals.

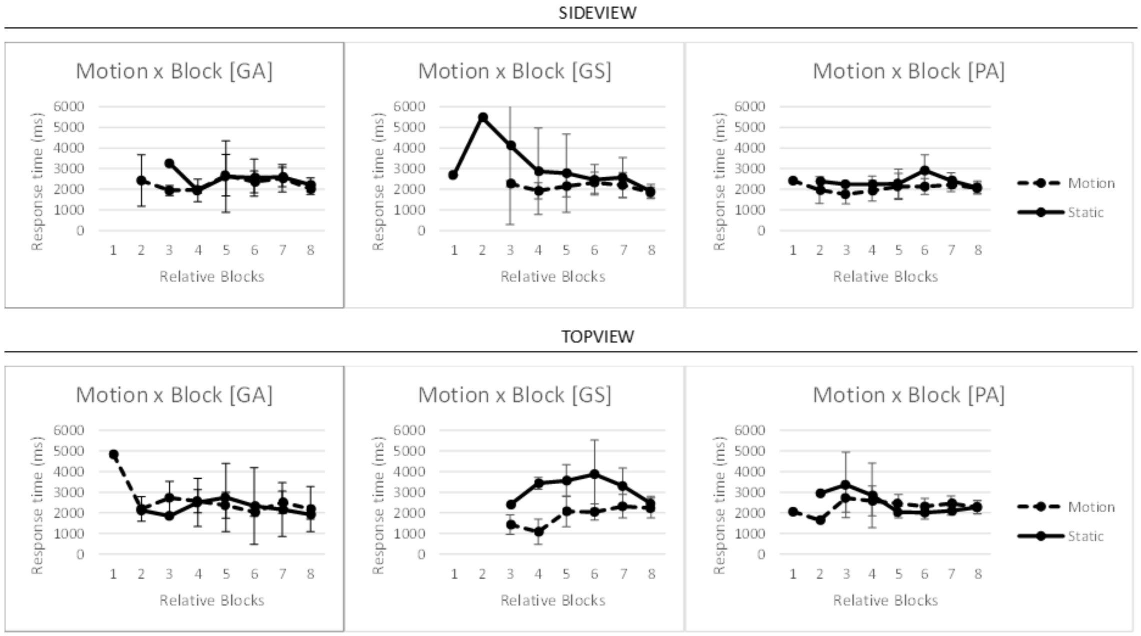

Figure B.14 *The View x Motion x Prime x NewBlock interaction for response times.*

Error bars indicate 95% confidence intervals.

APPENDIX C – IRB Approval Letter

Office *of*
Research Integrity

THE UNIVERSITY OF SOUTHERN MISSISSIPPI.

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NOTICE OF INSTITUTIONAL REVIEW BOARD ACTION

The project below has been reviewed by The University of Southern Mississippi Institutional Review Board in accordance with Federal Drug Administration regulations (21 CFR 26, 111), Department of Health and Human Services regulations (45 CFR Part 46), and University Policy to ensure:

- The risks to subjects are minimized and reasonable in relation to the anticipated benefits.
- The selection of subjects is equitable.
- Informed consent is adequate and appropriately documented.
- Where appropriate, the research plan makes adequate provisions for monitoring the data collected to ensure the safety of the subjects.
- Where appropriate, there are adequate provisions to protect the privacy of subjects and to maintain the confidentiality of all data.
- Appropriate additional safeguards have been included to protect vulnerable subjects.
- Any unanticipated, serious, or continuing problems encountered involving risks to subjects must be reported immediately. Problems should be reported to ORI via the Incident submission on InfoEd IRB.
- The period of approval is twelve months. An application for renewal must be submitted for projects exceeding twelve months.

PROTOCOL NUMBER:	22-159
PROJECT TITLE:	The Effects of Viewpoint, Motion, and Affordance Priming on Perceptual Learning of Feelies
SCHOOL/PROGRAM	School of Psychology
RESEARCHERS:	PI: Catherine Dowell Investigators: Dowell, Catherine~Hajnal, Alen~
IRB COMMITTEE ACTION:	Approved
CATEGORY:	Expedited Category
PERIOD OF APPROVAL:	14-Feb-2022 to 13-Feb-2023

Donald Sacco Jr.

Donald Sacco, Ph.D.
Institutional Review Board Chairperson

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