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Affordance Judgment for Collision or Bypass of Objects by Rotating Panels

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AFFORDANCE JUDGMENT FOR COLLISION OR BYPASS OF OBJECTS BY ROTATING PANELS

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ABSTRACT

We interact with rotating panels like doors in our day-to-day life. Doors afford the action of entry and exit from an enclosed space. Since a rotating door can pose a risk of collision to a person standing within the swept volume of the door, the ability to judge a safe distance from the door is imperative. The current study investigated the optical information available to judge whether a rotating panel would collide with or bypass a stationary object nearby. On a desktop computer, participants saw the top-down view of a door-like panel, which rotated about one of three different axes of rotation. A stationary object was placed at a certain distance, within or outside the swept volume of the panel. Analysis by Cabe (2019) shows that, as a panel rotates towards a nearby object, there is a definite pattern of change in the angle subtended on the object, by the edge of the panel moving towards the object. This study empirically tested whether participants utilize this optical information to judge an imminent collision or bypass. Results suggest that the pattern of change in angle helps observers in judging the event accurately. More importantly, the results also indicate that proper feedback can help in improving such affordance judgments.

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CHAPTER ONE

INTRODUCTION

Affordances

Gibson (1979) stated that the environment offers affordances to animals. Affordances can be considered as properties of objects and surfaces in the environment, which get actualized when an animal with a complementary property comes in contact with them (Turvey, 1992). Thus, for any animal, affordances are possibilities for action in the environment. For example, a ramp affords climbing when an animal having the ability to climb comes in contact with the ramp. Humans construct structures like walls, barriers and doors which control behavior in the environment, and thereby create different affordances or opportunities for action (Gibson, 1979; Cabe, 2019).

According to the Environmental Protection Agency, Americans spend about 90% of their time indoors (U.S. Environmental Protection Agency, 1989; Klepeis et al., 2001). This suggests that people spend a large amount of time interacting with artificial structures. Along with built walls and fences that constrain access to private spaces, doors and gates afford entry and exit to enclosures (Gibson, 1979). Today, diverse types of doors are available in the market. In addition to possibly being aesthetically pleasing, they all promise to improve our experience of moving in and out of enclosures. Maneuvering through doors and gates is such an integral part of our day-to-day life, that we do not usually pay attention to how we perform this activity. Ecological psychology focusses on the interaction between an organism and its environment, where information contained in ambient energy flow structured according to the laws of nature enables the organism to directly perceive its environment (Gibson, 1966, 1979). In the current study, some of the optical information available in perceiving the movement of a rectangular panel, akin to a door, has been explored.

Information for Perception

It is important to study the information that is available to the organism to understand what the surfaces of the environment affords them. According to Gibson (1979), organisms perceive invariant information that is revealed through their active exploration of the environment that surrounds them. The stimulus for vision is not a static image, but consists of optic flow (e.g., Gibson, 1950; Lee, 1980); a dynamic array of optical elements that change in accordance with movements of both environmental surfaces and the organism. The invariant pattern of information present in the optic flow is detected by organisms, and the human perceptual system is capable of attuning to the information relevant to particular actions that they intend to perform (Bingham & Pagano, 1998; Gibson, 1966; Lee 1976; Turvey, Shaw, Reed & Mace, 1981; Warren, 2006).

An example of such invariant information is time-to-contact, or tau, that specifies the time until an observer will be in contact with an object they are moving towards (Lee, 1976). The inverse of relative rate of expansion of the area covered on the retina by the object, tau specifies time-to-contact. The observer perceives this information without needing to perceive the lower order variables like distance or velocity, from which time-to-contact could be mathematically derived.

Gibson's suggestion that information in the ambient optic array is infinitely rich, led to some difficulty in understanding how humans picked the relevant information (Cutting, 1986). Although the mere presence of information in the optic array does not ensure its detection by the perceiver, perception cannot be fulfilled without such information. This problem has human factors implications in the design of built environments, where such informative structure should be prioritized. Cabe (2018) identified this issue and suggested some principles that can be followed to understand the available information in terms of its function to contribute to direct perception.

Affordance Perception in doors

Movement of doors is one event in the environment that is specified in the information structure ambient to the observer. Invariant patterns of information may be directly perceivable, which enables the observer to become aware of what the door affords them. The affordance of passability through an aperture by sliding doors has been subject to previous research (Bhargava et al., 2020, in press; Lucaites et al., 2020; Wagman & Taylor, 2005; Warren & Whang, 1987). Optical information available to perceive such apertures, as compared to obstacles like walls, was studied by Schmuckler and Li (1998). They found that texture expansion within the boundary of an obstacle, and deletion of texture on the background of the object, specified whether the obstacle was approaching. However, in the case of an aperture, texture expansion within the boundary of the aperture and accretion of texture on the background specified this.

Doorways that we usually encounter in built environments are very different from fixed or moving apertures. Cabe (2019) analytically identified a series of invariant information sources available in the case of doors rotating about a vertical axis of rotation. Such invariant information can specify the position of axis of rotation, the horizon line and even an apparent collision with an observer standing near the door. In previous work we have demonstrated that participants can use this information to perceive the position of axis of rotation (Raveendranath et al., under revision). In the current study, we explore whether individuals can make use of invariant information available to detect an apparent collision with a rotating door.

The most common type of doors that we see are the ones which have an axis of rotation along one of its side edges. However, there are other kinds of doors where the planar surface of the door extends to both sides of the axis of rotation (e.g. pivot doors, see Figure 1.1). In such cases, the position of the axis of rotation is not obvious. In the current study, we consider a panel which rotates about an axis of rotation at different positions. Recent work has been directed at the nesting of affordances. Some affordances are nested hierarchically within other affordances, with some affordances being subordinate and superordinate to each other, such as the graspability of pieces that can be assembled into a tool that will then afford some desired use (Wagman, Caputo & Stroffregen, 2016). The perception of whether or not one will be struck by a door could be superordinate to the perception of the door's axis of rotation.

Figure 1.1. A rotating panel for which the axis of rotation might not be immediately apparent (Retrieved from https://www.portapivot.com/). For other examples, see Cabe (2019).

Nested affordances are found to be perceived in social contexts too, where people can perceive the affordances available to another person in their close vicinity (Marsh, Richardson, Baron & Schmidt, 2006; Ramenzoni, Riley, Davis, Shockley & Armstrong, 2008; Wagman et al., 2016). For example, individuals can perceive the maximum jump height or reach height of another person standing near them based on the other person's action capabilities. It has also been found that people can perceive affordances for teleported robots (Jones, Johnson & Schmidlin, 2011; Moore, Gomer, Pagano & Moore, 2009). Since individuals can make prospective judgments about a person-environment relationship from a third-person perspective, it could be interesting to see whether such judgments can be made for a detached object in the environment. In the current study, the participants judged whether a rotating panel would collide with or miss an object near the panel. Future studies will be directed at testing whether individuals can judge a panel collision with themselves or with an avatar in a virtual environment.

Cabe (2019) described the optical information available to observers to judge whether a rotating panel would collide with them or not. He pointed out that the information becomes available only as the panel rotates, not when it was stationary. That is, information is contained in the optic flow. The following analysis is based on the article by Cabe (2019), where he suggests that a person standing near a rotating door or panel, can judge whether the panel would collide with him/ her. This judgment would be based on the invariant pattern of the optical angle subtended by the edge of the door moving towards the observer, on the observer, with respect to the axis of rotation.

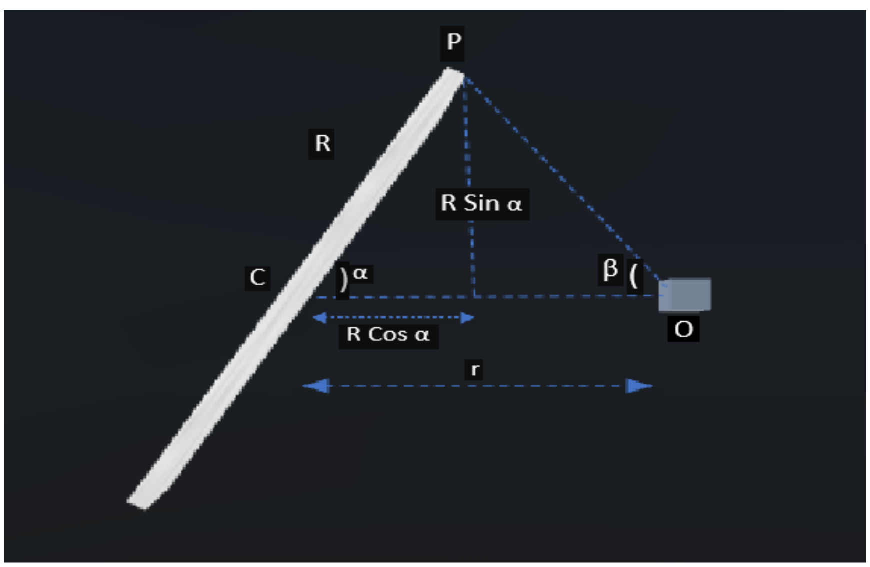


Figure 1.2. Top-down view of a panel rotating about an axis of rotation at C. An object O is at a position that may or may not be within the swept volume of the rotating panel.

Analysis of Information

Consider the top-down view of a panel rotating about a pivot axis, C (Figure 1.2). Object O is at a distance *r* from the pivot axis. Distance from the pivot axis to the tip of the panel that is moving towards the object is *R.* The angle of rotation with respect to the line connecting the object and the axis of rotation is α. The angle subtended by the part of the panel moving towards the object, on the object is β. The vertical component of the part of the panel rotating towards the object is, R Sin α. Similarly, the horizontal component is R Cos α. From this, Cot β can be expressed as below:

$$\cot \beta = ((r - R \cos \alpha) / R \sin \alpha) \qquad (1)$$

The numerator and denominator of the right-hand side of equation (1) can be divided by R, to get:

$$\cot \beta = (((r/R) - \cos \alpha) / \sin \alpha) \qquad (2)$$

From equation (2), angle β can be expressed as below:

$$\beta = \cot^{-1} (((r/R) - \cos \alpha) / \sin \alpha) \qquad (3)$$

From equation (3), it can be seen that angle β depends on the rotation angle α and the proportion r/R. If $r/R > 1$, the object will be outside the swept volume of the panel and the panel will bypass the object. If $r/R < 1$, the object will be within the swept volume of the panel and the panel will collide with the object. The pattern of change of β is invariant depending on the proportion of r/R. When $r/R > 1$, β will increase from the initial angle subtended, until it gets to a maximum value, which is less than 90°, and then it starts reducing till it gets to 0° (Figure 1.3). When $r/R < 1$, β will increase from the initial angle subtended past 90°, until it gets close to 180°, at which point a collision occurs (Figure 1.4).

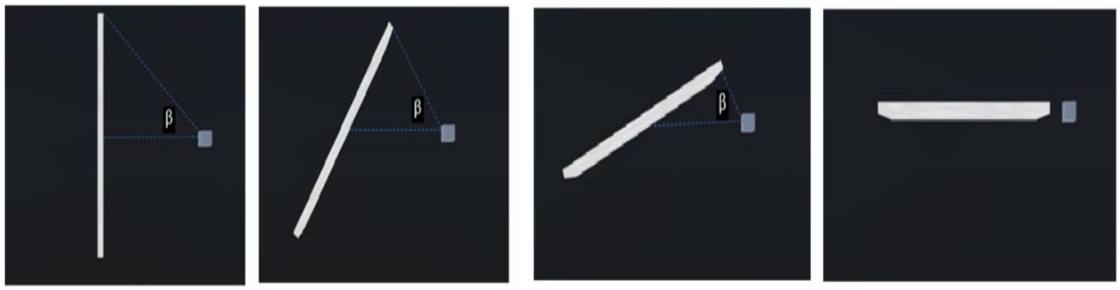


Figure 1.3. The case where the panel bypasses the stationary object.

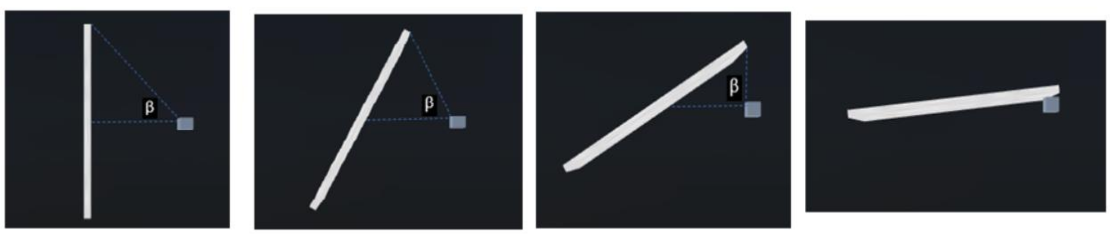


Figure 1.4. The case where the panel collides with the stationary object.

It is to be noted here that the information specifying a collision or bypass is the invariant pattern of change in the angle β. That is, if individuals attune to the pattern of β increasing and then possibly decreasing, then they can perceive whether the door will collide with or bypass the object. If β increases to a maximum value of less than 90° before reducing, then the panel will bypass the stationary object. Similarly, β increasing non-linearly to 180° indicates collision.

Consider the panel in Figure 1.3 to be 2 meters long and that it rotates about a pivot point at the middle of the panel. An object is placed at a distance of 1.4 meters from the axis point. The part of the panel that moves towards the object is 1 meter in length and therefore, the panel will bypass the object as it completes the rotation. In this case, the panel rotation angle (α) changes from 90° to 0°, while the angle subtended on the object (β) first increases to 50° and then decreases to 0° as it bypasses the object (Figure 1.5). If on the other hand, the object is placed at a distance of 0.5 meters from the axis point, the panel would collide with the object as it rotates. In this case, as the panel rotation angle (α) changes from 90° to 0°, the angle subtended on the object (β) increases to 180° non-linearly, colliding with the object (Figure 1.5).

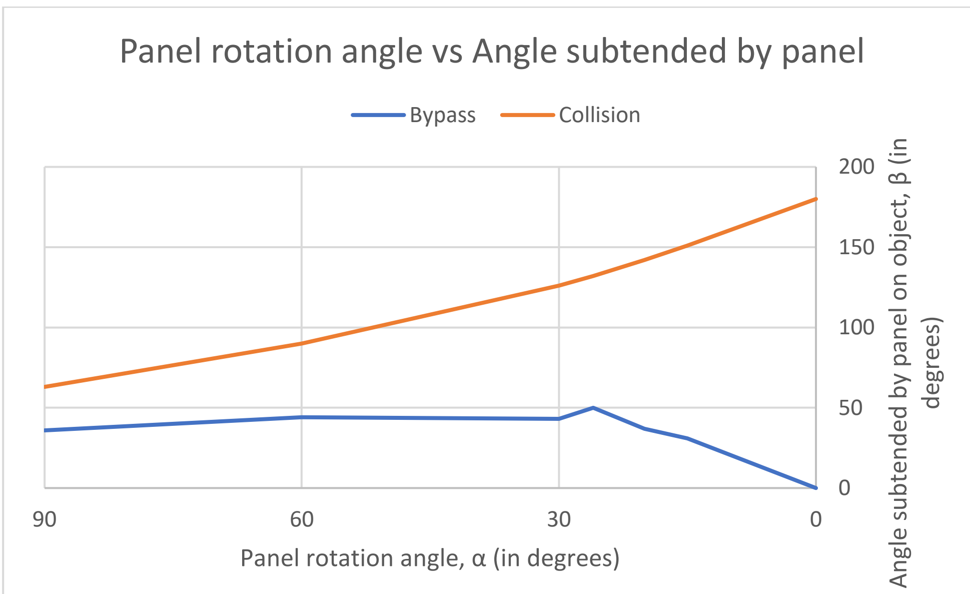


Figure 1.5. The change in angle subtended by the panel on the object (β) corresponding to the change in panel rotation angle (α). Rotation of the panel is from left to right in the figure.

If β exceeds 90° at any time, it means that the panel will collide with the object. Although there might not be any information available to make a metric judgment of this angle, perceptual learning might play a role here. So, 90° can be considered as a critical angle that observers get attuned to.

Present Study

The current study investigates whether individuals can accurately judge whether a panel rotating about a certain axis would collide with or bypass a nearby object, based on the invariant pattern of change in the angle subtended on the object, by the part of the panel moving towards the object. Further, this study also investigates whether individuals get attuned to the critical angle of 90° over time. As per the initial analysis of information described earlier, there is no information to judge a collision accurately until the panel subtends a critical angle of 90°.

Participants completed three phases: a pretest, a calibration and a posttest. The angle subtended on the object, by the edge of the panel moving towards the object, was manipulated in the experiment. When the object was within the swept volume of the panel, the panel rotated until this angle became 85°, 90° or 95°. When the object was outside the swept volume of the panel, the panel rotated to some maximum value and then reduced to zero. So, the panel rotated until the angle subtended on the object gets to: a) 5° less than the maximum value while the angle is steadily increasing, b) a maximum value (less than 90°), or c) 5° less than the maximum value while the angle is steadily decreasing. The distance between the object and the axis of rotation of the panel was also manipulated. Participants judged whether the panel would collide with or miss the object. Their response time to make each judgment was also recorded.

The main hypotheses for the study are as below:

H1: Participants' judgments will be faster and more accurate when β rotates past the critical angle in both collision and bypass events. In collision event, 90° is the critical angle, while in bypass case, the critical angle is the maximum angle subtended by the edge of the panel moving towards the stationary object, on the object, before starting to reduce to 0°.

H2: The accuracy of judgment will be better and response time will be faster in the posttest compared to the pretest phase.

CHAPTER TWO

METHOD

Participants

19 Clemson University undergraduate students participated in this study for partial course credit. A power analysis using effect size, *f* of 0.25 (Cohen, 1988) and an alpha of 0.05 revealed that a sample size of 20 would produce power greater than 0.9. This study incorporated a repeated measures design where each participant completed all three phases of the experiment.

Apparatus

The experiment was conducted using a desktop computer with a monitor of resolution of 1920 x 1080 and refresh rate of 60 Hz. The Unity game engine was used to design the experiment. Participants sat at a comfortable distance of 50 cm to 100 cm from the monitor so that they could easily press the buttons on the keyboard attached to the computer.

Participants saw the top-down view of a Unity scene with a rectangular panel object having a simulated length of 2 meters and a width 1 meter. A cubic object of 0.2-meter length, width and height was placed near the panel, either on the right or towards the left side of the panel (Figure 2.1). The panel rotated at an angular velocity of 100 degrees per second, about a certain axis of rotation on each trial. On top-down view, the axis of rotation of the panel could be at the bottom edge of the panel, at the midpoint between the bottom edge and the middle of the panel, or at the middle of the panel. This means that the proportion of the panel that swung towards the stationary object in each case was 1, 0.75 and 0.5 respectively. The scene was viewed from a camera placed at a simulated 7 meters away from the panel, rendering a top-down view of the scene.

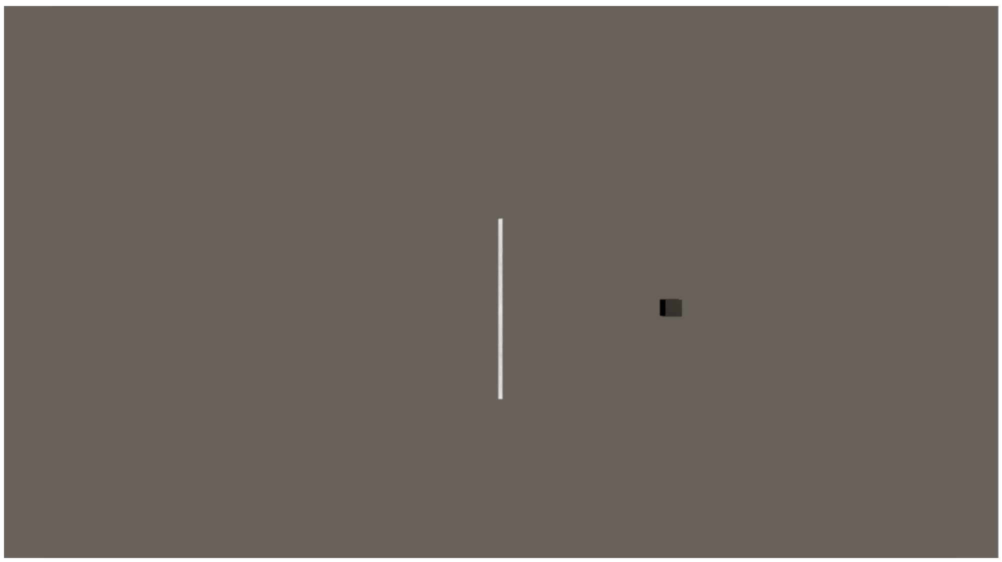


Figure 2.1. An example Unity scene that participants view on desktop computer.

Procedure

The experiment was divided into three phases: pretest, calibration and posttest. On each trial in the pretest phase, the participant saw the panel rotating about a certain pivot axis, towards the object. Corresponding to each position of the axis of rotation, there was a collision case and bypass case. Depending on whether it is a collision or bypass case, the distance between the axis of rotation and the object was adjusted. In effect, there were 6 different distances at which the object was placed (see Table 2.1). When the stationary object was at 1.97 meters, 1.48 meters or 1 meter from the pivot axis, the swinging panel collided with the object, and when it was at 1.77 meters, 1.4 meters or 2.33 meters from the axis, the panel missed the object.

Table 2.1

Pivot Axis	Distance (in meters)	Collision/Bypass
0	2.33	Bypass
0	1.97	Collision
0.25	1.77	Bypass
0.25	1.48	Collision
0.5	1.4	Bypass
0.5	1	Collision

If the object fell within the swept volume of the part of the panel moving towards the object, the panel rotated until the angle subtended by the edge of the panel moving towards the object, on the object, became 85°, 90° or 95°. If the object was outside the swept volume of the part of the panel moving towards the object, the panel rotated until the angle subtended by the edge moving towards the object, on the object, reached a maximum value (less than 90°), or 5° less than this maximum value. For example, when the axis of rotation is between the edge and the middle of the panel and the object is at a distance of 1.77 meters away from the axis of rotation, the angle subtended by the edge of the panel on the object steadily increases as it rotates, until it subtends an angle of 63.6°, and then steadily decreases until it is 0°. This angle was manipulated in the experiment such that, in the first case, as it keeps increasing, the panel would stop rotating at 58.6° (5° less than the maximum angle of 63.6°). In the second case, the panel would stop rotating at 63.6° (maximum angle it can subtend on the object). After subtending 63.6° on the object, the angle subtended starts decreasing. So, in the last case, as the angle keeps decreasing, it will again subtend 58.6° (5° less than the maximum angle) for a second time and the panel would stop rotating at this point (Figure 2.2).

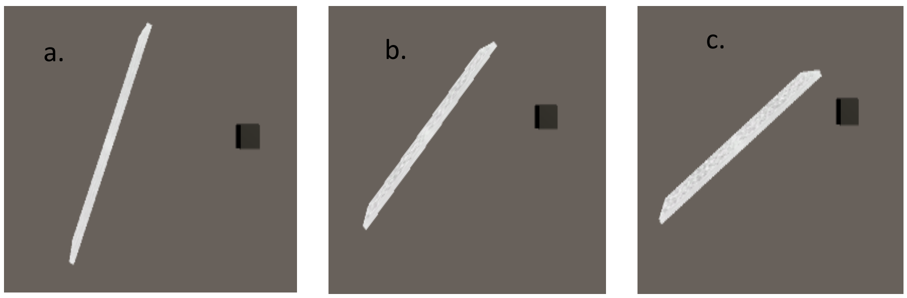


Figure 2.2. Three levels of β for bypass case. a) In the first case, the panel rotates, and the angle subtended by the top edge of the panel on the cube increases until it is 58.6°. b) In the second case, the panel rotates until the top edge subtends 63.6° on the cube. c) In the third case, the panel rotates, and the angle subtended by the top edge of the panel on the cube decreases until it is 58.6°.

As soon as the edge of the panel subtended the designated angle on the stationary object, it stopped rotating and after a pause of 30 milliseconds the participant saw a pop-up window, which blocked the panel and the object (Figure 2.3). The pop-up window had the question: "Will the panel collide with or miss the object?" There were two buttons below, with the words 'Collide' and 'Miss' written on them. The participant pressed the left arrow key on the keyboard to indicate collision and right arrow key to indicate a bypass event. The participants' response time to press the left or right arrow key was recorded in each trial. The whole animation, from the point when the panel starts swinging, till the time the pop-up window appears, took about 700 to 725 milliseconds in every trial.

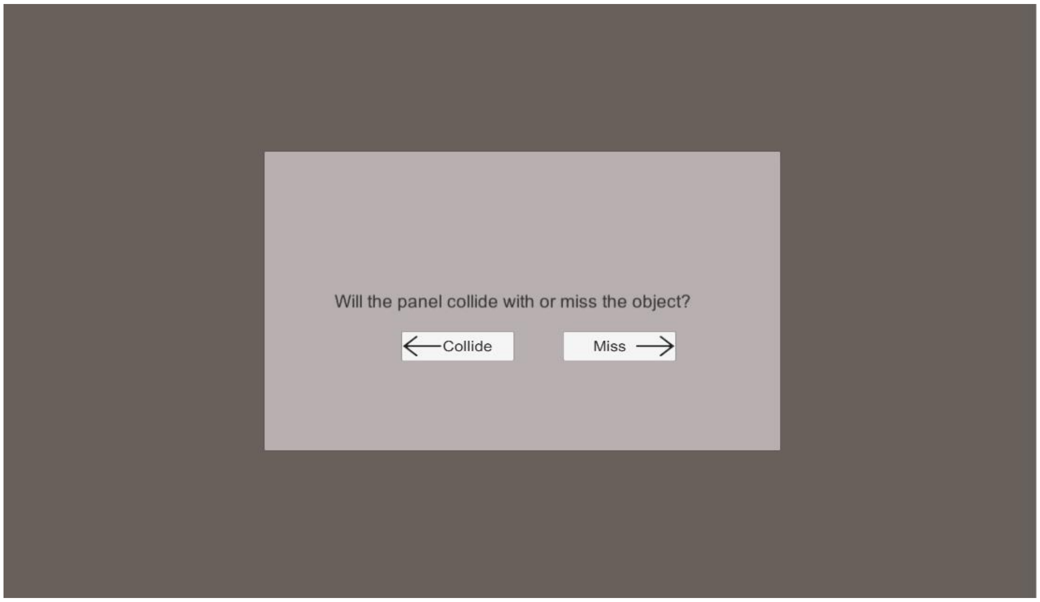


Figure 2.3. The pop-up window with the question.

In the calibration phase, the same procedure as described earlier for the pretest was followed. After the participant made the judgment, the pop up disappeared, and the panel started rotating again from where it started and continued swinging until it collided with or missed the stationary object. An explicit feedback was given to the participant about the collision or bypass event (Figure 2.4). The procedure followed in the posttest phase was the same as that in pretest phase.

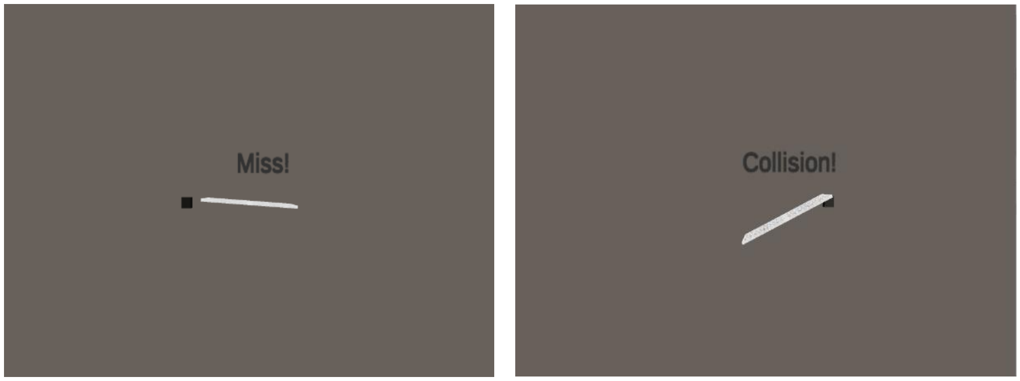


Figure 2.4. Feedback in calibration phase.

The five independent variables in the experiment are: The position of axis of rotation (3 levels), whether the trial is a collision or bypass case (2 levels), angle subtended on the object (3 levels), the phase (3 levels) and whether the stationary object was on the right or left side of the panel (2 levels). Using a completely within-subjects design, each participant completed 108 trials in the experiment presented in a random order. The accuracy (a binary variable indicating whether the participant made a correct or wrong judgment) and response time of the collision/ bypass judgment were the dependent variables.

CHAPTER THREE

RESULTS

Data Prep

Judgment accuracy. For each trial, participants' judgment accuracy was coded as whether they correctly judged the collision or bypass event. A correct judgment was coded as 'correct', and a wrong judgment was coded as 'wrong'.

Missing data. There were some trials that were skipped by participants, as they accidentally pressed the return key before providing a judgment for the event. In total, 3 trials (less than 0.01%) were missing.

Outlier analysis. Potential outliers were identified using the Mahalonobis distance. The distances were compared to a critical χ^2 value with one degree of freedom. Less than 1% of the data were identified as outliers as a result of this analysis.

Tests for normality. The participants' response time (RT) in each trial (measured in milliseconds) was plotted and tested for normality and was found to be skewed (Figure 3.1). The violation of normality assumption could result in an increased Type 1 error rate and decreased statistical power (Rosopa et al., 2013). Since this can result in a failure to detect results and possibly affect the conclusions of the study, a Box-Cox power transformation function was used to explore possible transformations for RT. It was found that an inverse transformation can be performed to accommodate for the skewness in RT.

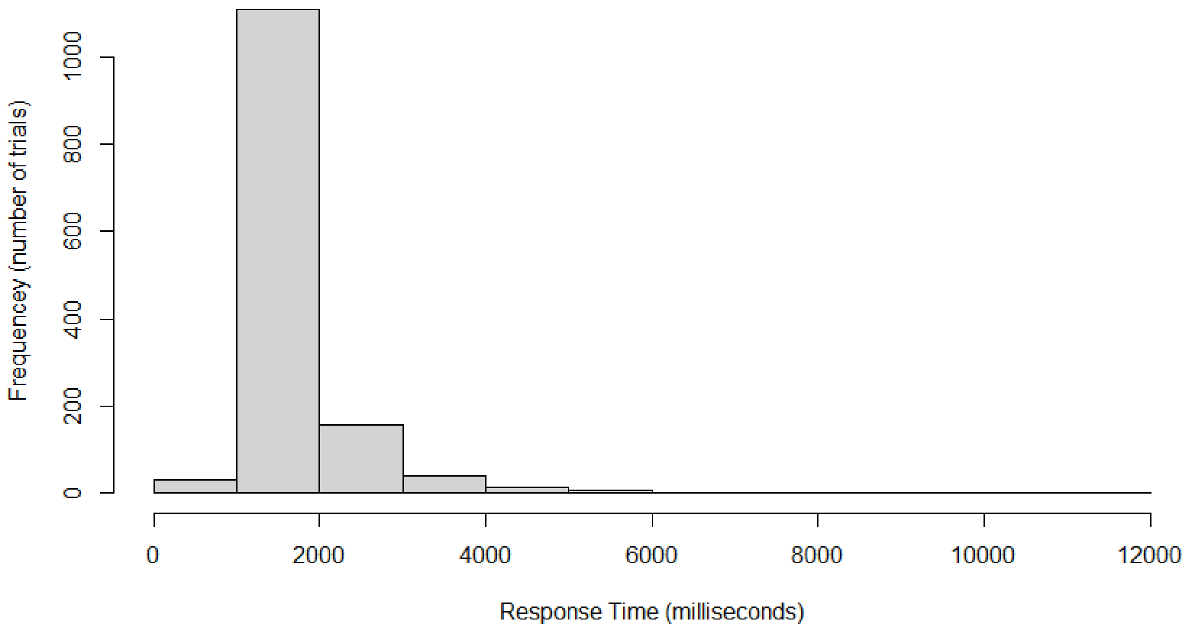


Figure 3.1. Distribution of Response Time for the pretest and posttest data.

Response Time

The following analysis contains only data from the pretest and posttest – where participants judged whether an event was a collision or bypass. Since RT was inverse transformed to account for the skewness of the data, the response variable used in the following analysis is the rate of trial completion (i.e., the unit of measurement is the number of trials completed per millisecond). Due to the repeated measures design of the experiment, variables had considerable nesting. That is, since each participant completed 108 trials, a portion of the variance in their responses can be attributed to a common source – the fact that the same participant was responding to each trial. Level 1 (within-participant) variables represent those that change from trial to trial (all the variables manipulated in this study were within-participant variables). Level 2 (between-participant) variables represent those that change from participant to participant (the Participant ID was the only between-participant variable in this study).

The null model (random intercept only model) was found to be statistically significant ($\chi^2 = 1153.3$, $p < 0.001$). The intraclass correlation coefficient for this model was calculated to be 0.211 indicating that approximately 21% of the total variance of the rate of trial completion (inverse of RT) was associated with the participant and that the assumption of independence was violated. Following a multilevel modeling technique would be ideal in this case. For all the following models, the only random effect computed was the intercept based on the Participant ID.

Model 1. To assess the effects of the angle subtended by the panel (β), the phase (pretest or posttest), the actual event (whether a collision or bypass), the position of axis of rotation of the panel and whether the stationary object was to the right or left side of the panel, all the independent variables were included in this model, without the interaction terms. That is, only the main effects of these variables were included in this model. The model explained 30.2% of the variance in rate of trial completion. A partial F test suggested that this model (AIC = -19948.33, df = 10) offered a significantly better fit to the data compared to the null model (AIC = -19798.71, df = 3), $p < 0.001$. See table 3.1 for omnibus test results for model 1.

The results suggest a significant effect of β on the rate of trial completion, χ^2 (2, N = 1365) = 69.86, $p < 0.001$, conditional $R^2 = 0.036$, marginal $R^2 = 0.036$. A post-hoc Tukey's HSD test showed that the rate of trial completion was significantly slower when β stopped before reaching critical value (*M* = 0.000647, *SD* = 0.0002), as compared to when it stopped at critical value (*M* = 0.000697, *SD* = 0.00017), $p < 0.001$ and when it stopped past the critical value (*M* = 0.000734, *SD* = 0.00018), $p < 0.001$.

There was also a significant effect of Phase on the rate of trial completion, χ^2 (1, N = 1365) = 78.20, $p < 0.001$, conditional $R^2 = 0.041$, marginal $R^2 = 0.04$. A post-hoc Tukey's HSD test showed that the rate of trial completion was significantly slower during pretest (*M* = 0.00065, *SD* = 0.00019), as compared to the posttest (*M* = 0.00073, *SD* = 0.00018), $p < 0.001$.

The position of the axis of rotation was also a significant predictor of the rate of trial completion, χ^2 (2, N = 1365) = 17.59, $p < 0.001$, conditional $R^2 = 0.01$, marginal $R^2 = 0.009$. A post-hoc Tukey's HSD test showed that the rate of trial completion was significantly slower when the panel rotated about an edge (*M* = 0.00067, *SD* = 0.00019), as compared to when it rotated about the midpoint of the panel (*M* = 0.00071, *SD* = 0.00019), $p < 0.001$.

There was also a significant effect of the position of the stationary object, on the rate of trial completion, χ^2 (1, N = 1365) = 6.66, $p = 0.01$, conditional $R^2 = 0.004$, marginal $R^2 = 0.003$. The rate of trial completion was significantly slower when the object was on the right side of the panel (*M* = 0.00068, *SD* = 0.0002) as compared to the left (*M* = 0.0007, *SD* = 0.00018).

Table 3.1
Omnibus test results for fixed effects predicting rate of trial completion in Model 1

Predictor	df1	N	χ^2
Angle (β)	2	1365	69.86***
Phase	1	1365	78.20***

Event	1	1365	1.765
Axis position	2	1365	17.59***
Stationary object position	1	1365	6.66**

note: *$p < .05$, **$p < .01$, ***$p < .001$

Model 2. To assess the effects of two-way interactions between the variables, all the main effects and two-way interactions were included in this model. The model explained 35.1% of the variance in rate of trial completion. A partial F test suggested that model 2 (AIC = -20006.95, df = 29) offered a significantly better fit to the data as compared to model 1 (AIC = -19948.33, df = 10), $p < 0.001$. See table 3.2 for omnibus test results for model 2.

Table 3.2

Omnibus test results for fixed effects predicting rate of trial completion in Model 2

Predictor	df1	N	χ^2
Angle (β)	2	1365	32.38***
Phase	1	1365	9.099**
Event	1	1365	0.582
Axis position	2	1365	1.53
Stationary object position	1	1365	1.46
Angle*Phase	2	1365	0.589
Angle*Event	2	1365	32.15***
Angle*Axis position	4	1365	2.44
Angle*Stationary object position	2	1365	2.13
Phase*Event	1	1365	2.47
Phase*Axis position	2	1365	0.62
Phase*Stationary object position	1	1365	0.12
Event*Axis position	2	1365	57.99***
Event*Stationary object position	1	1365	1.71
Axis position*Stationary object position	2	1365	0.16

note: *$p < .05$, **$p < .01$, ***$p < .001$

There was a significant two-way interaction between β and the actual event (see Figure 3.2), χ^2 (2, N = 1365) = 32.15, $p < 0.001$, $\omega^2 = 0.02$, conditional $R^2 = 0.016$, marginal $R^2 = 0.016$. When testing simple effects, when β stopped before reaching critical value, the rate of trial completion was found to be significantly different when the event was a collision (*M* = 0.00068, *SD* = 0.0002) as compared to when it was a bypass (*M* = 0.0006, *SD* = 0.0002), $p < 0.001$. Similarly, when β stopped past the critical value, the rate of trial completion was found to be significantly different when the event was a collision (*M* = 0.00071, *SD* = 0.00017) as compared to when it was a bypass (*M* = 0.00076, *SD* = 0.00019), $p = 0.005$. However, when β stopped at the critical value, the rate of trial completion was not found to be different in collision and bypass events.

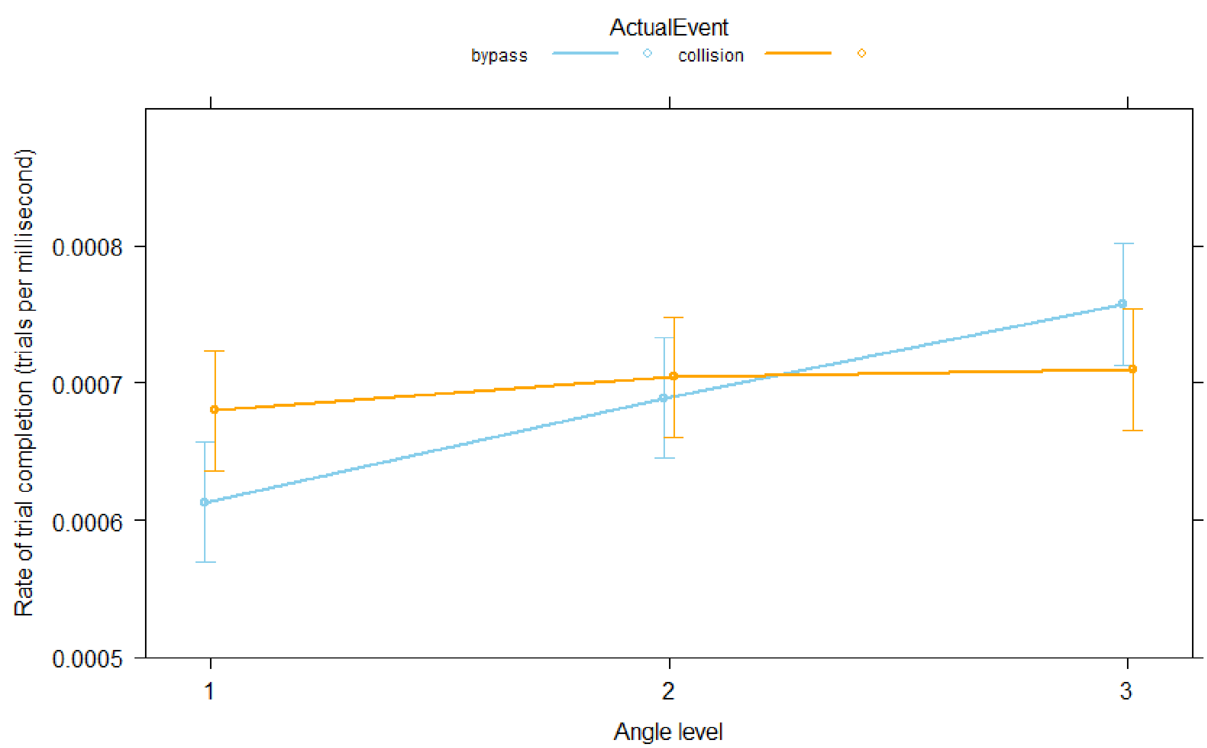


Figure 3.2. Interaction between Angle level (β) and the Event. Error bars indicate 95% confidence interval.

There was also a significant two-way interaction between the actual event and the position of the axis of rotation (see Figure 3.3), χ^2 (2, N = 1365) = 57.99, $p < 0.001$, conditional $R^2 = 0.029$, marginal $R^2 = 0.028$. When testing simple effects, when the panel rotated about an edge, the rate of trial completion was found to be significantly different when the event was a collision ($M = 0.00063$, $SD = 0.00018$) as compared to when it was a bypass ($M = 0.00071$, $SD = 0.00019$), $p < 0.001$. Similarly, when the panel rotated about its midpoint, the rate of trial completion was found to be significantly different when the event was a collision ($M = 0.00075$, $SD = 0.00016$) as compared to when it was a bypass ($M = 0.00068$, $SD = 0.0002$), $p < 0.001$. However, when the panel rotated about a point between the edge and the midpoint, the rate of trial completion was not found to be different in collision and bypass events.

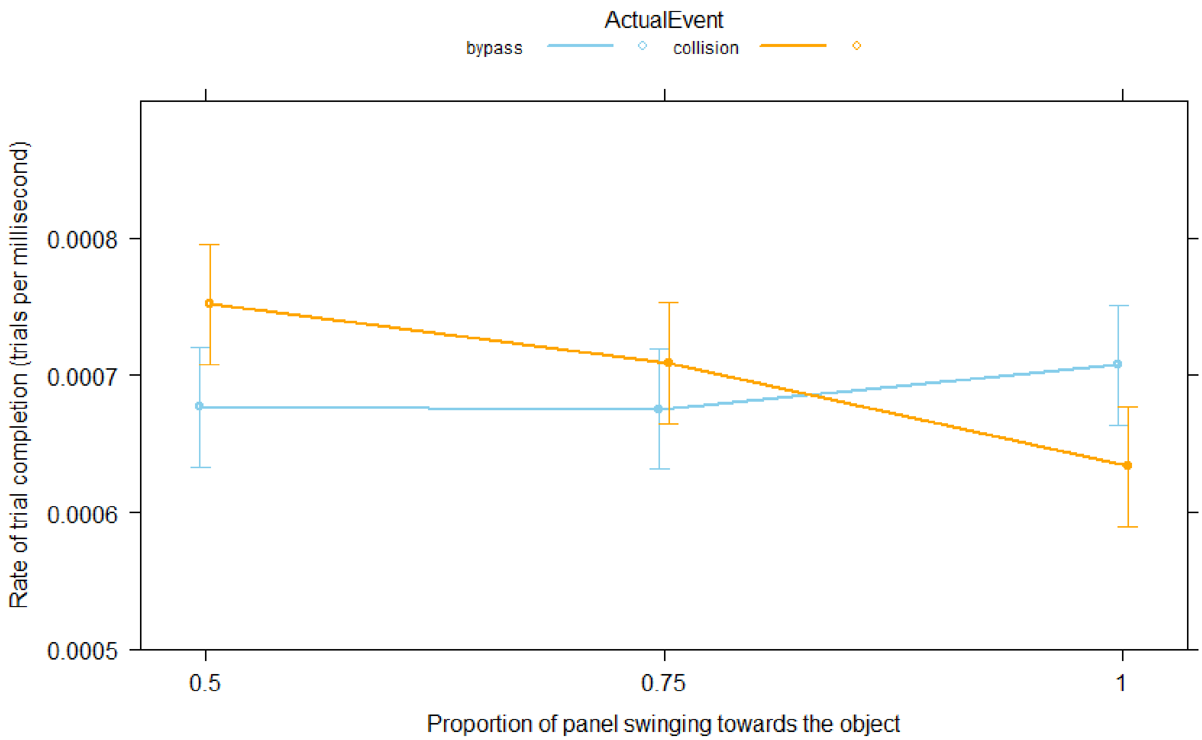


Figure 3.3. Interaction between Axis position and the Event. Error bars indicate 95% confidence interval.

Judgment Accuracy

Similar to the analysis for response time, the following analysis contains only data from the pretest and posttest – where participants judged whether an event was a collision or bypass. If the participant correctly judged an event as collision or bypass, the response was coded as 'correct', and if they were incorrect, the response was coded as 'wrong'. Similar to the previous analysis, because of the repeated measures design, a multilevel modeling approach was followed. Whether the participants judged the event correctly or incorrectly was the variable of interest in this case. Since this was a binary categorical variable, a binary logistic regression was used for the analysis.

The null model (random intercept only model) was found to be statistically significant ($\chi^2 = 231.49$, $p < 0.001$). The intraclass correlation coefficient for this model was calculated to be 0.099 indicating that approximately 10% of the total variance of the accuracy of judgment was associated with the participant and that the assumption of independence was violated. Following a multilevel modeling technique will be ideal in this case. For all the following models, the only random effect computed was the intercept based on the Participant ID.

Model 1. To assess the effects of the angle subtended by the panel (β), the phase (pretest or posttest), the actual event (whether a collision or bypass), the position of axis of rotation of the panel and whether the stationary object was to the right or left of the panel, all the independent variables were included in this model, without the interaction terms. That is, only the main effects of these variables were included in this model. Model 1 (AIC = 605.32, df = 10) offered a significantly better fit to the data than did the null model (AIC = 661.25, df = 3), $\chi^2 = 69.93$, $p < 0.001$. Also, model 1 explained 29.3% of the variance in the accuracy of judgment. See table 3.3 for omnibus test results for model 1.

The results suggest a significant effect of β on judgment accuracy, χ^2 (2, N = 1365) = 48.69, $p < 0.001$, conditional $R^2 = 0.159$, marginal $R^2 = 0.163$. Post-hoc pairwise comparisons showed that participants were significantly more likely to make a wrong judgment when β stopped at level 1 (*M probability* = 0.122, *SE* = 0.023), as compared to when it stopped at level 2 (*M probability* = 0.035, *SE* = 0.010), $z = 4.92$, $p < 0.001$ and level 3 (*M probability* = 0.016, *SE* = 0.006), $z = 5.81$, $p < 0.001$.

There was also a significant effect of Phase on judgment accuracy, χ^2 (1, N = 1365) = 7.56, $p = 0.006$, conditional $R^2 = 0.019$, marginal $R^2 = 0.02$. Participants were significantly more likely to make a wrong judgment in the pretest (*M probability* = 0.057, *SE* = 0.012) as compared to the posttest (*M probability* = 0.031, *SE* = 0.008).

It was found that the position of the axis, the position of the stationary object and the actual event were not significant predictors of judgment accuracy in model 1.

Table 3.3
Omnibus test results for fixed effects predicting rate of trial completion in Model 1

Predictor	df1	N	χ^2
Angle (β)	2	1365	48.69***
Phase	1	1365	7.56***
Event	1	1365	0.0175
Axis position	2	1365	1.83
Stationary object position	1	1365	2.19

note: *$p < .05$, **$p < .01$, ***$p < .001$

Model 2. To assess the effects of two-way interactions between the variables, all the main effects and two-way interactions were included in this model. Model 2 (AIC = 583.83, df = 29) offered a significantly better fit to the data as compared to model 1 (AIC = 605.32, df = 10), $\chi^2 = 59.495$, $p < 0.001$. Also, model 2 explains 52.1% of the variance in the accuracy of judgment. See table 3.4 for omnibus test results for model 2.

Table 3.4
Omnibus test results for fixed effects predicting rate of trial completion in Model 2

Predictor	df1	N	χ^2
Angle (β)	2	1365	2.15

Phase	1	1365	1.15
Event	1	1365	5.21*
Axis position	2	1365	7.07*
Stationary object position	1	1365	0.004
Angle*Phase	2	1365	4.62
Angle*Event	2	1365	0.29
Angle*Axis position	4	1365	5.18
Angle*Stationary object position	2	1365	0.685
Phase*Event	1	1365	0.61
Phase*Axis position	2	1365	0.58
Phase*Stationary object position	1	1365	0.12
Event*Axis position	2	1365	28.49**
Event*Stationary object position	1	1365	0.19
Axis position*Stationary object position	2	1365	2.29

note: *$p < .05$, **$p < .01$, ***$p < .001$

Although the omnibus test showed a significant main effect of the actual event and position of axis of rotation, further post hoc tests showed no significant difference in judgment accuracy based on these variables. However, there was a significant two-way interaction between the actual event and the position of the axis of rotation (see Figure 3.4), χ^2 (2, 1365) = 28.49, $p < 0.001$, conditional $R^2 = 0.086$, marginal $R^2 = 0.088$. When testing simple effects, when the panel rotated about an edge, the probability of making a wrong judgment was found to be significantly different when the event was a collision (*M probability* = 0.089, *SE* = 0.03) as compared to when it was a bypass (*M probability* = 0.014, *SE* = 0.008), $p < 0.001$. Similarly, when the panel rotated about its midpoint, the probability of making a wrong judgment was found to be significantly different when the event was a collision (*M probability* = 0.004, *SE* = 0.003) as compared to when it was a bypass (*M probability* = 0.037, *SE* = 0.017), $p < 0.001$. However, when the panel rotated about a point between the edge and the midpoint, the rate of trial completion was not found to be different in collision and bypass events.

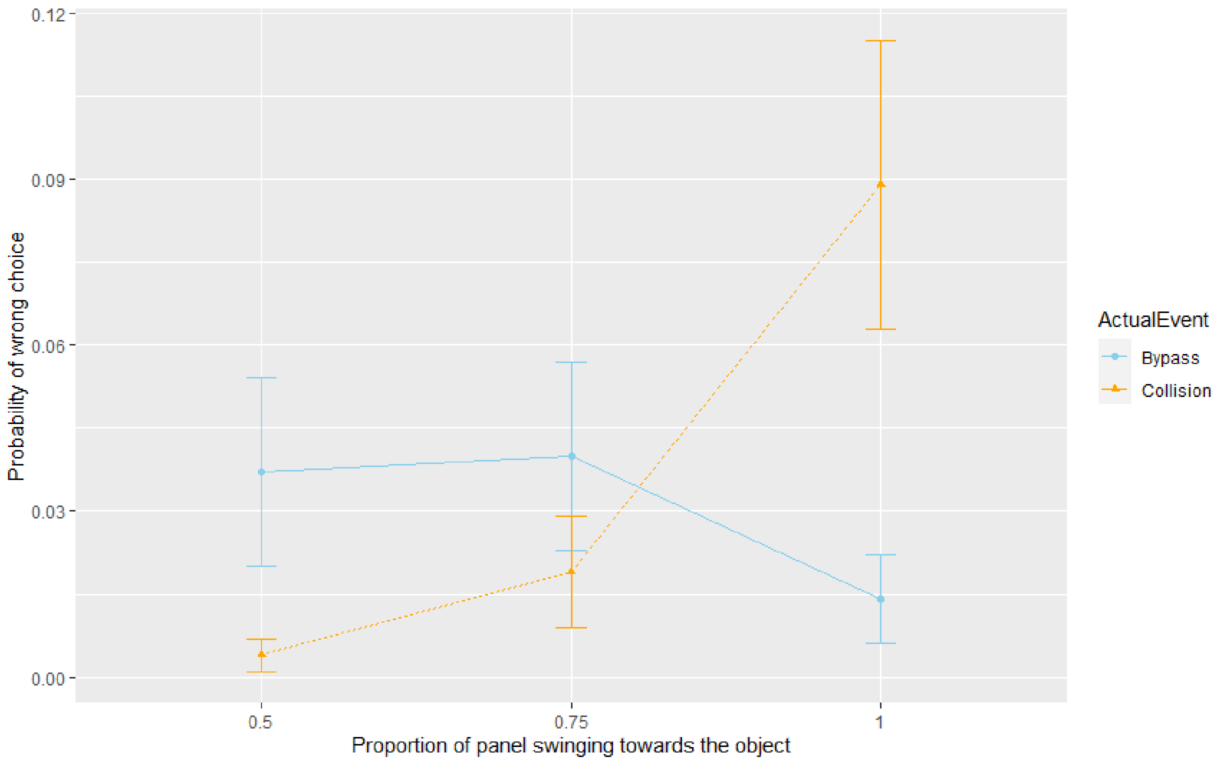


Figure 3.4. Interaction between Axis position and the Event. Error bars represents standard error of the mean.

CHAPTER FOUR

DISCUSSION

Ecological psychology emphasizes that the dynamic information in the stimulus array available to an organism forms the basis of its behavior. Gibson (1959) proposed that any transformation of the stimulus array (as a result of changes in the environment or active exploration of the organism) revealed invariant information, which directly specifies the state of the environment to the observer. According to Gibson's (1959, 1966, 1979) hypothesis, when investigating the perception of object or surface properties, the first step is to identify and measure optical (or acoustic, mechanical, etc.) parameters available in the stimulus array ambient to the organism that remain invariant across transformations. Based on this, one would expect that the perception of a given property is tied to one or more such invariants as opposed to other variables that fail to remain invariant over a transformation. That is, the task for investigators is to identify the invariant(s) to which the information underlying the perception of the object property is specific.

Following this strategy, Cabe (2019) identified the invariant pattern of change in the angle (β) subtended by the edge of a rectangular panel moving towards an observer, on the observer, with respect to the axis of rotation of the panel. If the observer is outside the swept volume of the panel, as the panel starts swinging towards the observer, β increases to some critical value less than 90° and then decreases till it becomes zero. However, if the observer is within the swept volume of the panel, β keeps increasing past

90°, till the panel collides with the observer at around 180°. Note that if β crosses 90° at any point, the observer can be certain that the panel will collide with them, but if β starts decreasing before it reaches 90°, the panel will miss the observer. Thus, the invariant pattern of change in β specifies to the observer, whether the rotating panel would collide with or miss the observer stationed near the panel. The goal of the current study was to empirically check whether participants utilize the same information to judge whether a swinging panel will collide with a stationary object near the panel, from a third person perspective. Once the panel started swinging towards the object, β increased until it stopped at one of the three levels. For collision event, the panel stopped swinging when β was 85°, 90° or 95°. For bypass event, it stopped swinging when β was: 1) 5° less than the critical value (as β was increasing), 2) at the critical value or 3) 5° less than the critical value (as β was decreasing back to 0°). Regardless of whether the event was a collision or bypass, the panel stopped swinging at one of the three levels of β. The participants' response time and accuracy measured in the experiment indicate that the identified invariant pattern affects how such judgments are made.

As hypothesized, when β stopped at 85° during the collision event, or when it stopped before it reached the critical value in the bypass case, the response time was found to be slower as compared to the other levels of β. However, it should be noted that the effect of β on the response time depended on whether the event was a collision or bypass. In the bypass event, when β stopped before the critical angle, participants' response time was slower, as compared to the collision event. However, when β stopped after rotating past the critical angle, response time was faster for the bypass event. The response time was almost the same for all three levels of β in the collision event. It is unclear what caused this interaction effect between the level of β and the event on just the response time and not the accuracy of judgment.

Participants had a higher probability of making a wrong judgment when β stopped prior to reaching the critical angle. This indicates that at this level of β, the information revealed was less salient for the participants to quickly and accurately judge whether the event was a collision or bypass, as compared to the other two levels of β. Although the probability of a wrong judgment was higher when the panel stopped swinging before β reached the critical value, participants were still accurate in a majority of trials (392 out of 455 trials), indicating that there could be factors other than the invariant pattern of change in β that help participants make the judgment. The participants' previous experience in making such judgments, the speed of transformation etc. could be some contributing factors. It is also possible that there is a difference in the rate of change of β in the case of a collision as compared to a bypass case, enabling the observer to accurately judge the event before β reaches the critical value. Future studies will explore whether participants can attune to any such information.

The phase of the experiment also affected the participants' judgment. Consistent with the hypothesis, participants were faster and more accurate in the posttest as compared to pretest. Previous research shows that participants with limited experience can get attuned to specific invariant information in the stimulus array, and even participants with a good amount of experience can improve their performance by calibrating to information in the environment (Altenhoff et al., 2012; Altenhoff, Pagano, Kil, & Burg, 2017; Bhargava et al., in press; Ebrahimi et al., 2014, 2015). In the current study, although the response time was slower and judgment accuracy was worse in the pretest phase, the feedback provided in the calibration phase helped participants in getting attuned to the invariant pattern of information. The participants' performance in the posttest reflects this improvement.

Interestingly, the response time was found to be slower when the stationary object was on the right side of the panel as compared to the left side. Although it is unclear whether the response method affected the RT, since the participants responded by pressing the left or right arrow key on the keyboard, it is possible that they had to inhibit the effect of direction on their response, to accurately judge the event. Further studies need to be conducted with different response methods to understand this better.

The proportion of the panel swinging towards the stationary object, R, affected the judgment, depending on whether the event was a collision or bypass. When the length of R included the whole panel, participants were faster and more accurate in judging the bypass case as compared to collision. On the other hand, when R was just half of the panel, participants were faster and more accurate in judging the collision event as compared to bypass. Since the panel rotated at an angular velocity of 100°/sec, the linear velocity of the edge swinging towards the panel was 3.49 m/s if R formed the whole length of the panel. Similarly, the linear velocity of the edge swinging towards the object was 1.745 m/s if R was just half of the panel. This means that when the linear velocity of the edge swinging towards the object was faster, participants found it easier to judge the bypass condition more quickly and accurately, and when the linear velocity of the edge was slower, it was easier to judge the collision condition. If participants judge based on the change in β, it is possible that detecting whether β crossed the critical angle of 90° is easier when the linear velocity of the edge swinging towards the object is slower. After the experiment, when participants were asked whether they focused on anything in particular that they saw on screen while judging the event, many of them answered that they followed the movement of the edge swinging towards the stationary object. Some participants also reported that it was easier to judge the trials with reduced panel rotation speed (perhaps referring to the slower linear velocity of the edge). Future studies should systematically explore the relationship between the linear velocity of the edge of the panel and participants' judgment.

Affordance judgment for collision or bypass from a third person perspective can also be explored in terms of Fitts' law (Fitts, 1954). According to Fitts' law, the time required to move a pointer to a specific target space is dependent on the distance to the target space and its size. While judging a collision or bypass as a third person, the distance between the rotating panel and the stationary object, along with the size of the stationary object could play a role in the judgment. Although the current study did not manipulate the size of the stationary object, future studies should consider this factor.

Cabe (2019) proposed that as a panel rotates, information exists for perceiving its axis of rotation, its frontal-parallel orientation and even the horizon line. This enables the observer to make judgments concerning affordances of the person-plus-door system. For this reason, it is important to understand what optical information is available, in order to optimize the design of built environments and ensure the safety of people who are exposed to such environments (e.g., Pagano, Day & Hartman, 2021). The current study explored whether the observer could detect information specifying whether an object is within the swept volume of a swinging door. This informs the observer as to whether an object of interest or another person will collide with the swinging door if they remain stationary in the current location. Future studies should explore whether observers can detect the same invariant information to judge the distance they should keep from a swinging door.

In summary, the current study demonstrates that when a swinging panel rotates towards a stationary object, the change in angle subtended on the object, by the edge of the panel moving towards the object helps a nearby observer in accurately judging the event. It also indicates that a simple calibration phase with appropriate feedback can help in improving such judgments. In particular, the results confirm the existence of invariant information in such transformations, and that observers can perceive these invariants. This provides more evidence to support Gibson's (1959, 1966, 1979) proposal that humans have the ability to detect invariants that are specific to features of the environment.

APPENDIX A

R Code for the analysis

1) Analysis of RT

```
library(data.table) #This package has the function rbindlist, which is
used to create a single table from multiple csv files.
multmerge = function(path){
  filenames=list.files(path=path, full.names=TRUE)
  rbindlist(lapply(filenames, fread))
}
path <- "C:/Users/Balagopal/Desktop/Clemson/Sem4/Thesis/data"
DF <- multmerge(path)
DF$Axis <- NA
DF$Axis <- ifelse(DF$Distance == 1.97, 0, DF$Axis)
DF$Axis <- ifelse(DF$Distance == 2.33, 0, DF$Axis)
DF$Axis <- ifelse(DF$Distance == 1.48, 0.25, DF$Axis)
DF$Axis <- ifelse(DF$Distance == 1.77, 0.25, DF$Axis)
DF$Axis <- ifelse(DF$Distance == 1.4, 0.5, DF$Axis)
DF$Axis <- ifelse(DF$Distance == 1.00, 0.5, DF$Axis)
```

Removing the calibration phase

```
DF <- subset(DF, DF$Phase != 'Calib')
```

Removing trials missed by participants

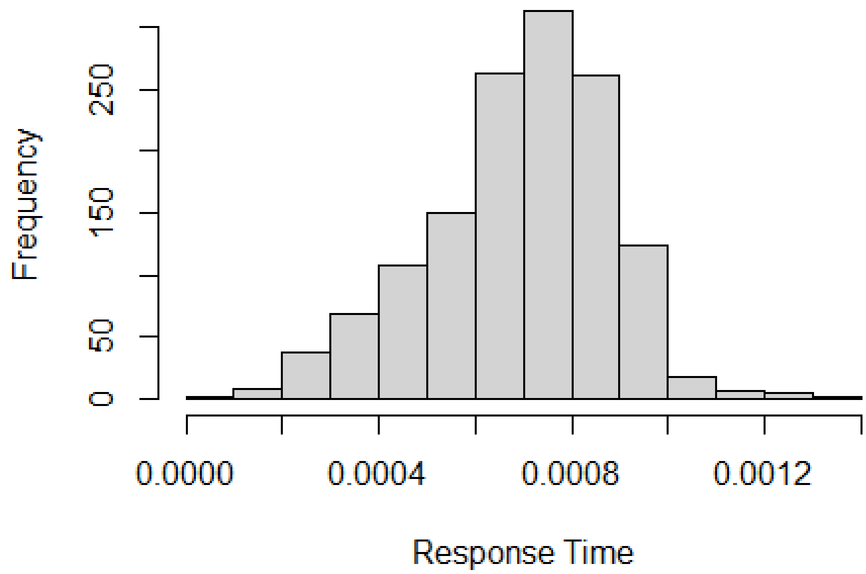
```
DF <- subset(DF, DF$RT != 0)
DF$Phase <- factor(DF$Phase)
DF$Angle <- factor(DF$Angle)
DF$ObjectPosition <- factor(DF$ObjectPosition)
DF$Result <- factor(DF$Result)
DF$Axis <- factor(DF$Axis)
DF$SubjectID <- factor(DF$SubjectID)
DF$ActualEvent <- factor(DF$ActualEvent)
summary(DF)
```

```
##      Block          TrialInBlock       Trial          Phase        Dis
tance
##  Min.   :0.0000   Min.   : 0.00   Min.   :  0.00   Post:682   Min.
:1.000
##  1st Qu.:0.0000   1st Qu.: 9.00   1st Qu.: 18.00   Pre :683   1st Qu
.:1.400
##  Median :0.0000   Median :18.00   Median : 35.00              Median
:1.770
##  Mean   :0.9993   Mean   :17.52   Mean   : 53.49              Mean
:1.659
##  3rd Qu.:2.0000   3rd Qu.:27.00   3rd Qu.: 90.00              3rd Qu
```

```
.:1.970
##  Max.   :2.0000   Max.   :35.00   Max.   :107.00             Max.
:2.330
##
##  Angle   ObjectPosition       RT           Choice              Actual
Event
##  1:455   left :682      Min.   :  766   Length:1365        bypass
:683
##  2:456   right:683      1st Qu.: 1209   Class :character   collision
:682
##  3:454                  Median : 1400   Mode  :character
##                         Mean   : 1621
##                         3rd Qu.: 1716
##                         Max.   :11581
##
##      Result     Completed         Attempts  Skipped           RespTi
me
##  correct:1274   Mode:logical   Min.   :1   Mode :logical   Min.   :
1.067
##  wrong  :  91   TRUE:1365      1st Qu.:1   FALSE:1365      1st Qu.:
1.667
##                                Median :1                   Median :
1.920
##                                Mean   :1                   Mean   :
2.220
##                                3rd Qu.:1                   3rd Qu.:
2.385
##                                Max.   :1                   Max.   :1
4.187
##
##       Age          SubjectID      Gender             Axis
##  Min.   :18.0   subject10: 72   Length:1365        0   :455
##  1st Qu.:18.0   subject11: 72   Class :character   0.25:456
##  Median :19.0   subject13: 72   Mode  :character   0.5 :454
##  Mean   :19.1   subject14: 72
##  3rd Qu.:20.0   subject15: 72
##  Max.   :23.0   subject16: 72
##                 (Other)  :933

library(car) #This package has the Anova function.

## Loading required package: carData

library(performance) #Used to call the icc function for intra class cor
relation coefficient.
library(sjstats) #Used to call r2 function to obtain the conditional an
d marginal R-squared values.
```

```
## Registered S3 methods overwritten by 'lme4':
##   method                          from
##   cooks.distance.influence.merMod car
##   influence.merMod                car
##   dfbeta.influence.merMod         car
##   dfbetas.influence.merMod        car

##
## Attaching package: 'sjstats'

## The following objects are masked from 'package:performance':
##
##     icc, r2

library(emmeans) #Used for emmeans function for obtaining estimated mar
ginal means.
library(effects) #Used for plotting graphs

## lattice theme set by effectsTheme()
## See ?effectsTheme for details.

library(nlme) #Used to call the gls and lme functions used to fit model
s.
library(lme4) #Used for the glmer function for performing binary logist
ic regression.

## Loading required package: Matrix

##
## Attaching package: 'lme4'

## The following object is masked from 'package:nlme':
##
##     lmList

summary(powerTransform(DF$RT~1))

## bcPower Transformation to Normality
##    Est Power Rounded Pwr Wald Lwr Bnd Wald Upr Bnd
## Y1    -1.419       -1.42      -1.5646      -1.2734
##
## Likelihood ratio test that transformation parameter is equal to 0
##  (log transformation)
##                              LRT df       pval
## LR test, lambda = (0) 457.1165  1 < 2.22e-16
##
## Likelihood ratio test that no transformation is needed
##                              LRT df       pval
## LR test, lambda = (1) 1689.294  1 < 2.22e-16
```

```
hist((DF$RT)^-1, xlab = "Response Time", main = "")
```



Inverse transform of RT

```
DF$RTinv <- (DF$RT)^-1
```

Null model

```
RTmodel1 <- gls(RTinv ~ 1, data = DF, method = "ML", na.action = "na.om
it")
```

Model with random slope

```
RTmodel2 <- lme(RTinv ~ 1, data = DF, method = "ML", na.action = "na.om
it", random = ~1|SubjectID)
anova(RTmodel1, RTmodel2)

##          Model df       AIC       BIC   logLik   Test  L.Ratio p-val
ue
## RTmodel1     1  2 -19534.83 -19524.39 9769.416
## RTmodel2     2  3 -19798.71 -19783.05 9902.354 1 vs 2 265.8761  <.00
01

icc(RTmodel2)
```

```
## Warning: 'icc' is deprecated.
## Use 'performance::icc()' instead.
## See help("Deprecated")
```

```
## # Intraclass Correlation Coefficient
##
##      Adjusted ICC: 0.211
##   Conditional ICC: 0.211
```

Model with just the main effects

```
RTmodel3 <- lme(RTinv ~ Angle+Phase+ActualEvent+Axis+ObjectPosition, da
ta = DF, method = "ML", na.action = "na.omit", random = ~1|SubjectID)
Anova(RTmodel3, type = "III")
```

```
## Analysis of Deviance Table (Type III tests)
##
## Response: RTinv
##                   Chisq Df Pr(>Chisq)
## (Intercept)    820.4428  1  < 2.2e-16 ***
## Angle           69.8591  2  6.765e-16 ***
## Phase           78.1961  1  < 2.2e-16 ***
## ActualEvent      1.7651  1  0.1839866
## Axis            17.5924  2  0.0001513 ***
## ObjectPosition   6.6631  1  0.0098430 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
anova(RTmodel2, RTmodel3)
```

```
##          Model df       AIC       BIC   logLik   Test L.Ratio p-valu
e
## RTmodel2     1  3 -19798.71 -19783.05 9902.354
## RTmodel3     2 10 -19948.33 -19896.14 9984.164 1 vs 2 163.621  <.000
1
```

Model including two-way interactions

```
RTmodel4 <- lme(RTinv ~ (Angle+Phase+ActualEvent+Axis+ObjectPosition)^2
, data = DF, method = "ML", na.action = "na.omit", random = ~1|SubjectI
D)
Anova(RTmodel4, type = "III")
```

```
## Analysis of Deviance Table (Type III tests)
##
## Response: RTinv
##                                 Chisq Df Pr(>Chisq)
## (Intercept)                  536.3823  1  < 2.2e-16 ***
## Angle                         32.3827  2  9.294e-08 ***
```

```
## Phase                         9.0992  1   0.002557 **
## ActualEvent                   0.5818  1   0.445624
## Axis                          1.5272  2   0.465991
## ObjectPosition                1.4590  1   0.227085
## Angle:Phase                   0.5891  2   0.744865
## Angle:ActualEvent            32.1489  2  1.045e-07 ***
## Angle:Axis                    2.4378  4   0.655816
## Angle:ObjectPosition          2.1256  2   0.345484
## Phase:ActualEvent             2.4652  1   0.116394
## Phase:Axis                    0.6203  2   0.733333
## Phase:ObjectPosition          0.1170  1   0.732334
## ActualEvent:Axis             57.9909  2  2.555e-13 ***
## ActualEvent:ObjectPosition    1.7054  1   0.191587
## Axis:ObjectPosition           0.1592  2   0.923467
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
anova(RTmodel3, RTmodel4)
```

```
##          Model df       AIC       BIC    logLik   Test  L.Ratio p-va
lue
## RTmodel3     1 10 -19948.33 -19896.14  9984.164
## RTmodel4     2 29 -20006.95 -19855.60 10032.475 1 vs 2 96.62218  <.0
001
```

Post-hoc analysis

```
options(scipen=999)
emmeans(RTmodel3, pairwise~Angle)
```

```
## $emmeans
##  Angle   emmean        SE df lower.CL upper.CL
##  1     0.000647 0.0000213 18 0.000602 0.000691
##  2     0.000697 0.0000213 18 0.000652 0.000742
##  3     0.000734 0.0000213 18 0.000689 0.000779
##
## Results are averaged over the levels of: Phase, ActualEvent, Axis, O
bjectPosition
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast   estimate        SE   df t.ratio p.value
##  1 - 2    -0.0000501 0.0000105 1339 -4.779  <.0001
##  1 - 3    -0.0000871 0.0000105 1339 -8.302  <.0001
##  2 - 3    -0.0000370 0.0000105 1339 -3.530  0.0012
##
## Results are averaged over the levels of: Phase, ActualEvent, Axis, O
```

```
bjectPosition
## Degrees-of-freedom method: containment
## P value adjustment: tukey method for comparing a family of 3 estimat
es
```

```
emmeans(RTmodel3, pairwise~Phase)
```

```
## $emmeans
##  Phase   emmean        SE df lower.CL upper.CL
##  Post  0.000730 0.0000209 18 0.000686 0.000774
##  Pre   0.000655 0.0000209 18 0.000611 0.000699
##
## Results are averaged over the levels of: Angle, ActualEvent, Axis, O
bjectPosition
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast    estimate         SE   df t.ratio p.value
##  Post - Pre 0.0000755 0.00000856 1339 8.817   <.0001
##
## Results are averaged over the levels of: Angle, ActualEvent, Axis, O
bjectPosition
## Degrees-of-freedom method: containment
```

```
emmeans(RTmodel3, pairwise~Axis)
```

```
## $emmeans
##  Axis   emmean        SE df lower.CL upper.CL
##  0    0.000671 0.0000213 18 0.000626 0.000715
##  0.25 0.000692 0.0000213 18 0.000647 0.000737
##  0.5  0.000714 0.0000213 18 0.000670 0.000759
##
## Results are averaged over the levels of: Angle, Phase, ActualEvent,
ObjectPosition
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast     estimate        SE   df t.ratio p.value
##  0 - 0.25   -0.0000214 0.0000105 1339 -2.040  0.1032
##  0 - 0.5    -0.0000439 0.0000105 1339 -4.182  0.0001
##  0.25 - 0.5 -0.0000225 0.0000105 1339 -2.145  0.0813
##
## Results are averaged over the levels of: Angle, Phase, ActualEvent,
ObjectPosition
## Degrees-of-freedom method: containment
```

```
## P value adjustment: tukey method for comparing a family of 3 estimat
es
```

```
emmeans(RTmodel3, pairwise~ObjectPosition)
```

```
## $emmeans
##  ObjectPosition   emmean        SE df lower.CL upper.CL
##  left           0.000703 0.0000209 18 0.000659 0.000747
##  right          0.000681 0.0000209 18 0.000637 0.000725
##
## Results are averaged over the levels of: Angle, Phase, ActualEvent,
Axis
## Degrees-of-freedom method: containment
## Confidence level used: 0.95
##
## $contrasts
##  contrast     estimate         SE   df t.ratio p.value
##  left - right 0.000022 0.00000856 1339 2.574   0.0102
##
## Results are averaged over the levels of: Angle, Phase, ActualEvent,
Axis
## Degrees-of-freedom method: containment
```

```
simple.angle1 <- lm(RTinv~ActualEvent, subset=Angle==1, DF)
summary(simple.angle1)
```

```
##
## Call:
## lm(formula = RTinv ~ ActualEvent, data = DF, subset = Angle ==
##     1)
##
## Residuals:
##        Min         1Q     Median         3Q        Max
## -0.0005928 -0.0001313  0.0000304  0.0001377  0.0006755
##
## Coefficients:
##                        Estimate Std. Error t value             Pr(>|
t|)
## (Intercept)          0.00061320 0.00001312  46.747 < 0.0000000000000
002 ***
## ActualEventcollision 0.00006663 0.00001853   3.596             0.000
359 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.0001976 on 453 degrees of freedom
## Multiple R-squared:  0.02775,    Adjusted R-squared:  0.0256
## F-statistic: 12.93 on 1 and 453 DF,  p-value: 0.0003592
```

```r
simple.angle2 <- lm(RTinv~ActualEvent, subset=Angle==2, DF)
summary(simple.angle2)
```

```
##
## Call:
## lm(formula = RTinv ~ ActualEvent, data = DF, subset = Angle ==
##     2)
##
## Residuals:
##        Min         1Q     Median         3Q        Max
## -0.0005714 -0.0001005  0.0000134  0.0001208  0.0004667
##
## Coefficients:
##                          Estimate Std. Error t value            Pr(>|t
|)
## (Intercept)            0.00068923 0.00001147  60.077 <0.0000000000000000
02 ***
## ActualEventcollision 0.00001499 0.00001622   0.924               0.3
56
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.0001732 on 454 degrees of freedom
## Multiple R-squared:  0.001876,   Adjusted R-squared:  -0.0003229
## F-statistic: 0.8531 on 1 and 454 DF,  p-value: 0.3562
```

```r
simple.angle3 <- lm(RTinv~ActualEvent, subset=Angle==3, DF)
summary(simple.angle3)
```

```
##
## Call:
## lm(formula = RTinv ~ ActualEvent, data = DF, subset = Angle ==
##     3)
##
## Residuals:
##         Min          1Q      Median          3Q         Max
## -0.00062361 -0.00010963  0.00001352  0.00013813  0.00054809
##
## Coefficients:
##                           Estimate  Std. Error t value             Pr(
>|t|)
## (Intercept)             0.00075739  0.00001194  63.426 < 0.00000000000
00002 ***
## ActualEventcollision -0.00004743  0.00001692  -2.803               0.
00529 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## Residual standard error: 0.0001803 on 452 degrees of freedom
## Multiple R-squared:  0.01708,    Adjusted R-squared:  0.01491
## F-statistic: 7.855 on 1 and 452 DF,  p-value: 0.005287
```

```
aggregate(RTinv ~ Angle + ActualEvent, data=DF, function(x) c(mean = me
an(x), sd = sd(x)))
```

```
##   Angle ActualEvent   RTinv.mean     RTinv.sd
## 1     1      bypass 0.0006131954 0.0001940729
## 2     2      bypass 0.0006892269 0.0001828252
## 3     3      bypass 0.0007573889 0.0001892734
## 4     1   collision 0.0006798239 0.0002011165
## 5     2   collision 0.0007042126 0.0001630724
## 6     3   collision 0.0007099556 0.0001707872
```

```
simple.axis0 <- lm(RTinv~ActualEvent, subset=Axis==0, DF)
summary(simple.axis0)
```

```
## 
## Call:
## lm(formula = RTinv ~ ActualEvent, data = DF, subset = Axis == 
##     0)
## 
## Residuals:
##         Min          1Q      Median          3Q         Max 
## -0.00058966 -0.00010667  0.00002459  0.00012604  0.00051802 
## 
## Coefficients:
##                         Estimate  Std. Error t value             Pr(
>|t|)
## (Intercept)           0.00070747  0.00001236  57.249 < 0.00000000000
00002 ***
## ActualEventcollision -0.00007323  0.00001750  -4.186            0.00
00341 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Residual standard error: 0.0001866 on 453 degrees of freedom
## Multiple R-squared:  0.03724,    Adjusted R-squared:  0.03511
## F-statistic: 17.52 on 1 and 453 DF,  p-value: 0.00003415
```

```
simple.axis0.25 <- lm(RTinv~ActualEvent, subset=Axis==0.25, DF)
summary(simple.axis0.25)
```

```
## 
## Call:
## lm(formula = RTinv ~ ActualEvent, data = DF, subset = Axis == 
##     0.25)
```

```
##
## Residuals:
##         Min          1Q      Median          3Q         Max
## -0.00062158 -0.00010765  0.00002599  0.00013240  0.00061331
##
## Coefficients:
##                         Estimate Std. Error t value            Pr(>|t
|)
## (Intercept)          0.00067535 0.00001237  54.596 <0.00000000000000
02 ***
## ActualEventcollision 0.00003328 0.00001749   1.902              0.05
78 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.0001868 on 454 degrees of freedom
## Multiple R-squared:  0.007908,   Adjusted R-squared:  0.005723
## F-statistic: 3.619 on 1 and 454 DF,  p-value: 0.05775

simple.axis0.5 <- lm(RTinv~ActualEvent, subset=Axis==0.5, DF)
summary(simple.axis0.5)

##
## Call:
## lm(formula = RTinv ~ ActualEvent, data = DF, subset = Axis ==
##     0.5)
##
## Residuals:
##         Min          1Q      Median          3Q         Max
## -0.00053380 -0.00011134  0.00001191  0.00012163  0.00062821
##
## Coefficients:
##                         Estimate Std. Error t value             Pr(>|
t|)
## (Intercept)          0.00067727 0.00001215  55.734 < 0.0000000000000
002 ***
## ActualEventcollision 0.00007370 0.00001719   4.289             0.000
022 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.0001831 on 452 degrees of freedom
## Multiple R-squared:  0.0391, Adjusted R-squared:  0.03697
## F-statistic: 18.39 on 1 and 452 DF,  p-value: 0.000022

aggregate(RTinv ~ Axis + ActualEvent, data=DF, function(x) c(mean = mea
n(x), sd = sd(x)))
```

```
##   Axis ActualEvent   RTinv.mean     RTinv.sd
## 1    0      bypass 0.0007074708 0.0001947052
## 2 0.25      bypass 0.0006753523 0.0001955047
## 3  0.5      bypass 0.0006772691 0.0002014226
## 4    0   collision 0.0006342374 0.0001780828
## 5 0.25   collision 0.0007086319 0.0001776299
## 6  0.5   collision 0.0007509706 0.0001626960
```

2) Analysis of Judgment Accuracy

Null model

```
model1 <- glm(Result ~ 1,family = binomial(link="logit"),data = DF)
```

Model with random slope

```
model2 <- glmer(Result ~ 1 + (1 | SubjectID), data = DF, family = binom
ial(link="logit"), control = glmerControl(optimizer = "bobyqa"), nAGQ =
0)
lme4:::anovaLmer(model1, model2)

## Data: DF
## Models:
## model1: Result ~ 1
## model2: Result ~ 1 + (1 | SubjectID)
##        npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## model1    1 670.66 675.88 -334.33   668.66
## model2    2 661.25 671.69 -328.63   657.25 11.406  1  0.0007319 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

icc(model2)

## Warning: 'icc' is deprecated.
## Use 'performance::icc()' instead.
## See help("Deprecated")

## # Intraclass Correlation Coefficient
##
##      Adjusted ICC: 0.099
##   Conditional ICC: 0.099
```

Main effects model

```
model3 <- glmer(Result ~ Angle + Phase + ActualEvent + Axis + ObjectPos
ition + (1 | SubjectID), data = DF, family = binomial(link="logit"), co
ntrol = glmerControl(optimizer = "bobyqa"), nAGQ = 0)
Anova(model3, type = "III")
```

```
## Analysis of Deviance Table (Type III Wald chisquare tests)
##
## Response: Result
##                  Chisq Df      Pr(>Chisq)
## (Intercept)    45.5568  1 0.00000000001483 ***
## Angle          48.6898  2 0.00000000002674 ***
## Phase           7.5611  1        0.005964 **
## ActualEvent     0.0175  1        0.894646
## Axis            1.8302  2        0.400483
## ObjectPosition  2.1899  1        0.138920
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
anova(model2, model3)
```

```
## Data: DF
## Models:
## model2: Result ~ 1 + (1 | SubjectID)
## model3: Result ~ Angle + Phase + ActualEvent + Axis + ObjectPosition
+
## model3:     (1 | SubjectID)
##        npar    AIC    BIC  logLik deviance Chisq Df        Pr(>Chisq
)
## model2    2 661.25 671.69 -328.63   657.25
## model3    9 605.32 652.29 -293.66   587.32 69.93  7 0.00000000000152
6 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Model with two way interactions

```
model4 <- glmer(Result ~ (Angle + Phase + ActualEvent + Axis + ObjectPo
sition)^2 + (1 | SubjectID), data = DF, family = binomial(link="logit")
, control = glmerControl(optimizer = "bobyqa"), nAGQ = 0)
Anova(model4, type = "III")
```

```
## Analysis of Deviance Table (Type III Wald chisquare tests)
##
## Response: Result
##                             Chisq Df   Pr(>Chisq)
## (Intercept)               22.6016  1 0.0000019932 ***
## Angle                      2.1450  2      0.34215
## Phase                      1.1549  1      0.28252
## ActualEvent                5.2108  1      0.02245 *
## Axis                       7.0719  2      0.02913 *
## ObjectPosition             0.0044  1      0.94712
## Angle:Phase                4.6151  2      0.09950 .
## Angle:ActualEvent          0.2903  2      0.86488
```

```
## Angle:Axis                    5.1808  4      0.26924
## Angle:ObjectPosition          0.6848  2      0.71008
## Phase:ActualEvent             0.6108  1      0.43448
## Phase:Axis                    0.5795  2      0.74845
## Phase:ObjectPosition          0.1209  1      0.72806
## ActualEvent:Axis             28.4944  2 0.0000006494 ***
## ActualEvent:ObjectPosition   0.1944  1      0.65925
## Axis:ObjectPosition           2.2896  2      0.31829
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
anova(model3, model4)
```

```
## Data: DF
## Models:
## model3: Result ~ Angle + Phase + ActualEvent + Axis + ObjectPosition
+
## model3:     (1 | SubjectID)
## model4: Result ~ (Angle + Phase + ActualEvent + Axis + ObjectPositio
n)^2 +
## model4:     (1 | SubjectID)
##        npar    AIC    BIC  logLik deviance  Chisq Df  Pr(>Chisq)
## model3    9 605.32 652.29 -293.66   587.32
## model4   28 583.83 729.96 -263.91   527.83 59.495 19 0.000004651 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Post-hoc analysis

```
emmeans(model3,pairwise~Angle)
```

```
## $emmeans
##  Angle emmean    SE  df asymp.LCL asymp.UCL
##  1      -1.97 0.210 Inf     -2.38     -1.56
##  2      -3.32 0.287 Inf     -3.89     -2.76
##  3      -4.10 0.376 Inf     -4.84     -3.36
##
## Results are averaged over the levels of: Phase, ActualEvent, Axis, O
bjectPosition
## Results are given on the logit (not the response) scale.
## Confidence level used: 0.95
##
## $contrasts
##  contrast estimate    SE  df z.ratio p.value
##  1 - 2       1.353 0.275 Inf 4.922   <.0001
##  1 - 3       2.130 0.366 Inf 5.814   <.0001
##  2 - 3       0.777 0.413 Inf 1.881   0.1442
##
```

```
## Results are averaged over the levels of: Phase, ActualEvent, Axis, O
bjectPosition
## Results are given on the log odds ratio (not the response) scale.
## P value adjustment: tukey method for comparing a family of 3 estimat
es
```

```
emmeans(model3,"Angle",type = "response")
```

```
##  Angle   prob      SE  df asymp.LCL asymp.UCL
##  1     0.1223 0.02255 Inf   0.08449    0.1737
##  2     0.0347 0.00961 Inf   0.02011    0.0594
##  3     0.0163 0.00602 Inf   0.00787    0.0334
##
## Results are averaged over the levels of: Phase, ActualEvent, Axis, O
bjectPosition
## Confidence level used: 0.95
## Intervals are back-transformed from the logit scale
```

```
emmeans(model3,pairwise~Phase)
```

```
## $emmeans
##  Phase emmean    SE  df asymp.LCL asymp.UCL
##  Post   -3.45 0.261 Inf     -3.96     -2.94
##  Pre    -2.81 0.230 Inf     -3.26     -2.36
##
## Results are averaged over the levels of: Angle, ActualEvent, Axis, O
bjectPosition
## Results are given on the logit (not the response) scale.
## Confidence level used: 0.95
##
## $contrasts
##  contrast   estimate    SE  df z.ratio p.value
##  Post - Pre   -0.642 0.233 Inf -2.750  0.0060
##
## Results are averaged over the levels of: Angle, ActualEvent, Axis, O
bjectPosition
## Results are given on the log odds ratio (not the response) scale.
```

```
emmeans(model3,"Phase",type = "response")
```

```
##  Phase   prob      SE  df asymp.LCL asymp.UCL
##  Post  0.0307 0.00775 Inf    0.0186    0.0501
##  Pre   0.0567 0.01232 Inf    0.0369    0.0863
##
## Results are averaged over the levels of: Angle, ActualEvent, Axis, O
bjectPosition
## Confidence level used: 0.95
## Intervals are back-transformed from the logit scale
```

```
emmeans(model4,pairwise~ActualEvent)

## NOTE: Results may be misleading due to involvement in interactions

## $emmeans
##  ActualEvent emmean    SE  df asymp.LCL asymp.UCL
##  bypass       -3.52 0.334 Inf     -4.18     -2.87
##  collision    -3.93 0.406 Inf     -4.72     -3.13
##
## Results are averaged over the levels of: Angle, Phase, Axis, ObjectP
osition
## Results are given on the logit (not the response) scale.
## Confidence level used: 0.95
##
## $contrasts
##  contrast           estimate    SE  df z.ratio p.value
##  bypass - collision    0.403 0.421 Inf 0.958   0.3381
##
## Results are averaged over the levels of: Angle, Phase, Axis, ObjectP
osition
## Results are given on the log odds ratio (not the response) scale.

emmeans(model4,"ActualEvent",type = "response")

## NOTE: Results may be misleading due to involvement in interactions

##  ActualEvent   prob      SE  df asymp.LCL asymp.UCL
##  bypass      0.0287 0.00929 Inf   0.01512    0.0537
##  collision   0.0193 0.00771 Inf   0.00882    0.0419
##
## Results are averaged over the levels of: Angle, Phase, Axis, ObjectP
osition
## Confidence level used: 0.95
## Intervals are back-transformed from the logit scale

emmeans(model4,pairwise~Axis)

## NOTE: Results may be misleading due to involvement in interactions

## $emmeans
##  Axis emmean    SE  df asymp.LCL asymp.UCL
##  0     -3.29 0.355 Inf     -3.98     -2.59
##  0.25  -3.50 0.380 Inf     -4.24     -2.75
##  0.5   -4.39 0.542 Inf     -5.45     -3.32
##
## Results are averaged over the levels of: Angle, Phase, ActualEvent,
ObjectPosition
## Results are given on the logit (not the response) scale.
## Confidence level used: 0.95
```

```
##
## $contrasts
##  contrast   estimate    SE  df z.ratio p.value
##  0 - 0.25      0.212 0.431 Inf 0.491   0.8756
##  0 - 0.5       1.101 0.585 Inf 1.881   0.1441
##  0.25 - 0.5    0.890 0.567 Inf 1.570   0.2586
##
## Results are averaged over the levels of: Angle, Phase, ActualEvent,
ObjectPosition
## Results are given on the log odds ratio (not the response) scale.
## P value adjustment: tukey method for comparing a family of 3 estimat
es

emmeans(model4,"Axis",type = "response")

## NOTE: Results may be misleading due to involvement in interactions

##  Axis   prob      SE  df asymp.LCL asymp.UCL
##  0    0.0360 0.01232 Inf   0.01830    0.0697
##  0.25 0.0294 0.01084 Inf   0.01415    0.0599
##  0.5  0.0123 0.00658 Inf   0.00427    0.0347
##
## Results are averaged over the levels of: Angle, Phase, ActualEvent,
ObjectPosition
## Confidence level used: 0.95
## Intervals are back-transformed from the logit scale

emmeans(model4, list(pairwise ~ ActualEvent + Axis), type = "response")

## $`emmeans of ActualEvent, Axis`
##  ActualEvent Axis    prob      SE  df asymp.LCL asymp.UCL
##  bypass      0    0.01414 0.00758 Inf  0.004913    0.0400
##  collision   0    0.08878 0.02585 Inf  0.049502    0.1542
##  bypass      0.25 0.04490 0.01719 Inf  0.020973    0.0935
##  collision   0.25 0.01909 0.00968 Inf  0.007017    0.0509
##  bypass      0.5  0.03677 0.01664 Inf  0.014971    0.0875
##  collision   0.5  0.00403 0.00318 Inf  0.000856    0.0187
##
## Results are averaged over the levels of: Angle, Phase, ObjectPositio
n
## Confidence level used: 0.95
## Intervals are back-transformed from the logit scale
##
## $`pairwise differences of ActualEvent, Axis`
##  1                             odds.ratio      SE  df z.ratio p.val
ue
##  bypass 0 / collision 0             0.147  0.0796 Inf -3.543  0.005
3
```

```
##  bypass 0 / bypass 0.25              0.305  0.1770 Inf -2.046  0.316
2
##  bypass 0 / collision 0.25           0.737  0.5388 Inf -0.418  0.998
4
##  bypass 0 / bypass 0.5               0.376  0.2411 Inf -1.526  0.647
6
##  bypass 0 / collision 0.5            3.545  3.4125 Inf  1.314  0.777
2
##  collision 0 / bypass 0.25           2.073  0.8750 Inf  1.726  0.514
1
##  collision 0 / collision 0.25        5.006  2.5716 Inf  3.136  0.021
2
##  collision 0 / bypass 0.5            2.553  1.2301 Inf  1.945  0.374
8
##  collision 0 / collision 0.5        24.082 18.8254 Inf  4.070  0.000
7
##  bypass 0.25 / collision 0.25        2.415  1.2712 Inf  1.676  0.548
0
##  bypass 0.25 / bypass 0.5            1.232  0.6538 Inf  0.392  0.998
8
##  bypass 0.25 / collision 0.5        11.619 10.1185 Inf  2.816  0.054
9
##  collision 0.25 / bypass 0.5         0.510  0.3268 Inf -1.051  0.900
5
##  collision 0.25 / collision 0.5      4.810  3.8130 Inf  1.982  0.352
8
##  bypass 0.5 / collision 0.5          9.434  6.7943 Inf  3.116  0.022
6
##
## Results are averaged over the levels of: Angle, Phase, ObjectPositio
n
## P value adjustment: tukey method for comparing a family of 6 estimat
es
## Tests are performed on the log odds ratio scale
```

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