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REAL OR RENDERED? DETERMINING HUMAN PREFERENCES IN AN EXTENDED REALITY ENVIRONMENT

by

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The Army and the Department of Defense (DoD) have a desire to bring extended reality (XR) technologies into both the training and operational environments. Augmented reality (AR) technology has moved to the forefront of this effort. This study had two goals. The first was to determine if humans have an instinctual preference in reacting to real or rendered objects while operating in an XR environment. The second was to determine whether military members have been conditioned, through training, to look or move to the left first. We hypothesized that humans would favor real objects over rendered objects, and military members would attend to their left side first. To investigate this, we developed an experiment in which the participants were given a search task in XR. Only two objects were placed in the room, a real and rendered cardboard box. The object preference was found to be significant, but not in the manner we had hypothesized. Overall, our results suggest that our participants tended to look left first (65% of the participants) and chose to interact with the rendered object first (87% of the participants). These findings indicate that further research is necessary to investigate the ecological implications of XR environments and human activities in them.

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REAL OR RENDERED? DETERMINING HUMAN PREFERENCES IN AN EXTENDED REALITY ENVIRONMENT

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ABSTRACT

The Army and the Department of Defense (DoD) have a desire to bring extended reality (XR) technologies into both the training and operational environments. Augmented reality (AR) technology has moved to the forefront of this effort. This study had two goals. The first was to determine if humans have an instinctual preference in reacting to real or rendered objects while operating in an XR environment. The second was to determine whether military members have been conditioned, through training, to look or move to the left first. We hypothesized that humans would favor real objects over rendered objects, and military members would attend to their left side first. To investigate this, we developed an experiment in which the participants were given a search task in XR. Only two objects were placed in the room, a real and rendered cardboard box. The object preference was found to be significant, but not in the manner we had hypothesized. Overall, our results suggest that our participants tended to look left first (65% of the participants) and chose to interact with the rendered object first (87% of the participants). These findings indicate that further research is necessary to investigate the ecological implications of XR environments and human activities in them.

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LIST OF ACRONYMS AND ABBREVIATIONS

2D	Two Dimensional
3D	Three Dimensional
AMSO	Army Modeling and Simulation Office
AR	Augmented Reality
BR	Blended Reality
C1	Condition One
C2	Condition Two
CFFT	Call for Fire Trainer
CFT	Cross Functional Teams
CPU	Central Processing Unit
CR	Conditioned Response
CS	Conditioned Stimulus
DLI	Defense Language Institute
DoD	Department of Defense
DV	Dependent Variable
GPU	Graphics Processing Unit
H0	Null Hypothesis
HA	Alternate Hypothesis
HMD	Head Mounted Display
HUD	Heads Up Display
IV	Independent Variable
IVAS	Integrated Visual Augmentation System
ML1	Magic Leap One
MOVES	Modeling Virtual Environments and Simulations
MR	Mixed Reality
NFL	National Football League
NPS	Naval Postgraduate School
OS	Operating System
SD	Standard Deviation
SIMD	Single Instruction, Multiple Data
SOF	Special Operation Forces
SSE2	Streaming SIMD Extension 2
UR	Unconditioned Response

US	Unconditioned Stimulus
VR	Virtual Reality
XR	Extended Reality
YoS	Years of Service

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I. INTRODUCTION

A. MOTIVATION

The head of the Army Modeling and Simulation Office (AMSO) asked the Modeling Virtual Environments and Simulations (MOVES) Institute at the Naval Postgraduate School (NPS) to investigate the interactions of humans while using augmented reality (AR) environments for purposes other than vehicle or equipment maintenance tasks. AR is a combination of computer-generated inputs onto a live view of the world. These inputs can include video, graphics, or sounds (Dhanendran, 2009). A new term, extended reality (XR), refers to the use of all or some elements of AR, virtual reality (VR), and mixed reality (MR). XR is a blending of all of these technologies together (Vera, 2019).

The use of XR technologies for training has become a desired state in the military and civilian environments (Freedberg, 2018). In March 2019, the Army submitted a request to industry for an AR device, initially called Heads-Up Display (HUD) 3.0, which has been rebranded to the Integrated Visual Augmentation System (IVAS). This request to industry led to a $480-million contract to be awarded for the production of this device. Also, the Army recently created a new Futures Command, which is comprised of several Cross Functional Teams (CFT), to help investigate and streamline the development and acquisition of new capabilities (Suits, 2018). Both the Synthetic Training Environment and the Soldier Lethality CFTs are highly interested in XR environments to enable warfighter training for current and future threats (Freedberg, 2018).

B. PROBLEM STATEMENT

New technology is being adopted before determining whether the human interaction with this technology is good or bad. The promise of new technology must be balanced with an eye towards the human user, the natural environment, and the organizational environment. Research is needed to understand and identify how human interactions at the most basic level; in this case, bias or instinct towards real vs. rendered objects will impact XR technology’s potential use in both a training and operational environment. This thesis is a move in that direction. The information provided by this thesis will help the Army and the Department of Defense (DoD) refine current and future requirements related to the use of XR technology.

C. THESIS OBJECTIVES

In this study, we investigate if humans have a preference to interact with real or rendered objects while in an XR environment.

This study also investigates if conditioning through training affects how humans behave under certain conditions. Specifically, we investigate if military members have been conditioned, through training, to look or move to the left first. This insight is valuable and could play a role in how objects are identified in a XR training or operational scenario.

D. RESEARCH QUESTIONS

This thesis has two goals. First, it will determine if humans demonstrate a preference of interaction concerning real or rendered objects in an XR environment. We hypothesize that humans in an XR environment will favor real objects over rendered objects (H0: $p = .50$, HA: $p > .50$). We believe this to be the case based on several observed behaviors while studying at NPS. These behaviors dealt with human bias and user interface design related to using XR technology.

Second, it will determine whether military members have been conditioned, through training, to look or move to the left first. We hypothesize that military members will look left first (H0: $p = .50$, HA: $p >.50$). At the start of military training, military members are trained in discipline and uniformity of movements. One of the first things new soldiers learn is how to march in formation, starting with the movement of their left foot first. Another example is when running, we train soldiers to run in step as a group, using cadences that key on the strike of the left foot with the ground; our cadences proceed (running or marching): left, right, left. Cadences are always called on the hit of the left foot (Department of the Army, 2012, p. 2–8). Room search patterns are taught left to right, up and down, or in the case of a “Z” pattern which also starts left to right (CALL, 2007, p.12).

E. SCOPE OF THE THESIS

The scope of this thesis is on the examination of human instinctual bias and conditioned behavior. The thesis's aim is to answer the fundamental question: Which type of objects, do humans interact with naturally: real or rendered? To answer this question, we need to eliminate as many confounds as possible. We have not induced any threat behavior within the environment. This thesis does not examine conscience choice behavior or cognitive load assessment. Environmental stress has not been placed on the participants. AR technology is not being evaluated; it is simply the tool being used to conduct the experiment. The desired end-state of this work is a foundation from which to build on, and for understanding how humans behave and are affected by extended reality environments.

F. ORGANIZATION OF THESIS

Chapter I provides the motivation, problem statements, research questions, and the scope of the thesis.

Chapter II discusses necessary definitions, background in AR/VR, literature review, and related works that helped to lay the groundwork for this thesis.

Chapter III examines the methodology and explains the study design, instruments used for the study, the procedures used during the study, and analytical assessment.

Chapter IV presents the results along with the demographics of the study participants.

Chapter V contains the discussion and the conclusion based on the data collected from the study and the research.

Chapter VI outlines future work and recommendations.

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II. BACKGROUND

A. DEFINITIONS

In this realm of technology, many terms need to be defined before moving forward. This section provides definitions of terms that are used throughout this thesis.

- **Augmented reality (AR):** Adding computer-generated digital sensory inputs to a live view. Inputs can include, but are not limited to video, graphics, or sound (Dhanendran, 2009).

- **Virtual reality (VR):** A three dimensional (3D), completely immersive, computer rendered world that shuts out the real world (Sherman, Sherman, and Craig 2003).

- **Mixed reality (MR):** The merging of AR and VR, to which the virtual objects are seen in the real world via an augmented reality head-mounted display (AR-HMD) and can be manipulated or interacted with by the user in real time (Gleb, 2017).

- **Extended reality (XR):** Which refers to the use of all or some elements of AR, VR and MR (Vera, 2019). XR can be thought of as blending all the technologies together.

- **Real object:** A physically real object in the real world that has size, shape and mass.

- **Rendered object:** A computer-generated virtual image that can only be seen while using an AR-HMD, or through computer software that allows AR-HMD mirroring.

For this thesis, the term AR specifically focuses on the ability of the device to display rendered objects in the real world; the term MR refers to the use of an AR device to render virtual objects, but the rendered objects can be manipulated or interacted with in real time.

B. CURRENT AND FUTURE MILITARY USES OF XR

Since XR spans across all domains of AR, VR, and MR, this section focuses on some of the current and potential future uses of AR and VR from both an operational and training perspective. This section is not a comprehensive list of all the current uses of AR and VR technology across the U.S. military, but it gives the reader a background on how this technology is currently being used within the military.

The use of VR can be seen across all branches of the U.S. military for training purposes. A great example of VR is best seen in the use of flight simulators for initial pilot training and to maintain their proficiency. VR flight simulators are used in a several different ways, from part task training on take-offs, landings, instrument-only flight, and emergency procedures, to full mission tactical training exercises (Lee, 2017).

Although not as well-known as flight simulators, vehicle simulators serve a vital role in the training of ground forces. They not only allow for driver training but they also support rehearsals and training. They serve as a way to train entire vehicle crews without the need for requesting range time or drawing weapons and ammunition (Ciccotti, 2016).

Another simulator created to assist with training of military personnel is the call for fire trainer (CFFT) (see Figure 1). This device assists in training forward observers on how to call in artillery fire on enemy positions.

Figure 1. Call for fire trainer (CFFT) immersive system
Source: U.S. Army (2019).

There are even skydiving parachute simulators (see Figure 2) to assist special force operators in conducting dry-run jumps, adverse weather jumps, training on challenging terrain, and malfunction drills dealing with airborne parachute operations (Joiner 2014).

Figure 2. Parachute simulator. Source: Joiner (2014).

Simulators allow for the conduct of training at a lower cost, higher repetition, less time, and in more varying situations than their real-world counterparts (Ciccotti 2016; Joiner 2014; Lee 2017). Unfortunately, adding technology to a problem space does not always produce results. One such example is the Army's attempt to take a proven desktop VR battlespace trainer, virtual battlespace (VBS3), and modify it for use in an HMD to render a virtual environment (VE). The result of this was a system called the Dismounted Soldier Training System (DSTS) (Baker, 2015). VBS3 is based on commercial gaming platforms that were modified to reflect real-world physics (Bohemia, 2018). DSTS's aim was to take VBS3 and make it more realistic by adding a computer backpack system, an HMD, and a weapon fitted with laser aiming devices to allow the user to move and experience activities as if they were conducting them in the real world. In this system, the weapon served a dual purpose as the movement controller and the weapon. The user could conduct the physical actions of standing, kneeling, going prone, aiming, and firing, and their avatar would do the same actions in the virtual world. A joystick on the side of the weapon allows the users avatar to move inside the VE. A downside to this implementation of VR is that the user is unable to physically move outside of a small space, in this case a three-foot circle. This project was short-lived due to the weight and heat the backpack computer added, and cybersickness from the unrealistic movement in the environment that many of the users experienced (Baker, 2015). As seen from previous examples, many physical constraints (allowable movement space, user interfaces [HMD/weapon]) have prevented VR, from moving from the training domain into the operational domain.

AR technology has the potential to be widely used in both the training and operational environments. Operationally, AR has been used for years in aviation helmets that have HUD information overlaid in real-time, on real world views (Newman, 2017). Conceptually the use of AR has been a goal for the military for many years (Livingston et al. 2002). It has not been until recently that the technology has matured enough to make this possible. The military has pushed industry to develop an AR system to assist with equipment and vehicle maintenance tasks to help solve the shortage of skilled maintenance technicians (Deal, 2018). These types of AR maintenance devices can have both a training and operational role. Aviation Companies such as Boeing have been at the forefront of implementing and integrating AR technology for aircraft maintenance. Boeing developed AR headsets that allow users to see the steps to take in a maintenance task, or to be able to virtually pull out a section of an engine and enlarge it to see potential issues. They also introduced a Smartglasses system into their wire harnessing plant that allowed users to not have to rely on switching back in forth between wiring and looking at a diagram in a document; the use of these glasses demonstrated a 25% increase in productivity (Sacco, 2016). Industry success with implementing AR has caused the military to increase interest in applying AR technology outside of maintenance. The Army tasked industry to develop an AR-HMD for use by dismounted soldiers. The IVAS is what the Army hopes will become the future of AR for dismounted troops. While only initially tested, the Army hopes that this technology will result in every soldier having and AR-HMD that can display real-time data on top of the real-world view (see Figure 3).

Figure 3. U.S. SOF testing IVAS. Source: South (2019).

The goal for this system is that it would allow for increased situational awareness (SA) and coordination between units, provide instant replay (during training), create virtual sandtables, thermal capabilities, and intelligence-updated maps, potentially merging several pieces of equipment into one device (South, 2019).

C. RESEARCH REVIEWED

1. AR User Studies

In searching for similar research to this study, we were unable to locate any previous research asking the same or a similar question about human instinctual tendencies related to rendered and real objects in an XR environment. A study by Swan and Gabbard (2005) examined peer-reviewed papers searching for studies involving AR. Their study is in no way an exhaustive or complete list of all AR studies; it is a representation of existing user-based AR studies. The results of their study showed that only 2% of all the 1,104 papers they reviewed described a formal user-based experiment. Taking their work, we wanted to see how our experiment would fit into their model of user-based studies.

When looking at prior types of AR-user studies, Swan and Gabbard developed a model that broke the user studies into three related areas: Perception, Performance/ Interaction, and Collaboration. They defined these areas as follows.

- Perception: how the user understands the visual information that is overlaid on the real world.
- Performance/Interaction: how, but not why, the user interacts with virtual information.
- Collaboration: how AR can be used to enhance face to face activity.

For this study, we only focus on perception and interaction-based user research.

We examined two perception studies: Livingston et al. (2003), and Ellis and Menges (1998). The research that Livingston conducted focused on the user's ability to accurately understand three layers of depth among large objects that were occluded from view. Within their study, they changed the objects' drawing style (wire, fill, wire+fill), their opacity, and intensity, along with their placement (near, medium and far). The results were that, even without perspective constraints, the style and opacity enabled the users to identify objects up to three layers deep. A similar perception study conducted by Ellis and Menges examined if the placement of virtual objects near real objects made a difference when it came to distance measuring. They discovered that users would underestimate the distance of a virtual object when it was near a real object.

Interaction studies like Mason et al. (2001) and Angelopoulos (2018) demonstrate the user's ability to interact with different elements of the AR environment. Mason explored the role that visual and haptic [tactile] feedback played, while interacting with virtual objects using a table-top AR environment. Results revealed that the need for haptic feedback is crucial for effective task performance. Angelopoulos's study compared efficiency and precision with and without AR cues. His study focused on the potential use of AR within the maintenance realm. Results from his study were that AR-cued results were more efficient than non-cued human placement, while precision was roughly equal.

Our study does not fall neatly into any of the categories previously listed, nor are we aware of any similar study that has been conducted. It is left to the reader to determine to which category from Swan and Gabbard (2005) our study belongs. It could be argued that it is a perception style study, because the investigation concerns the user's reaction to a real or rendered object. It could also be argued that, since the users were told that they would interact with an object during the experiment, even though they actually did not, that it is simply an interaction study. Alternatively, the experiment, as simple as it may seem, might be a kind of blurred mix of perception and interaction. From the other AR user studies, it is clear that other research must be examined to help explain our findings. Upon review of the problem space, it was decided to approach this study from an information processing perspective, using the human information processing model developed by Wickens (2003) (see Figure 4).

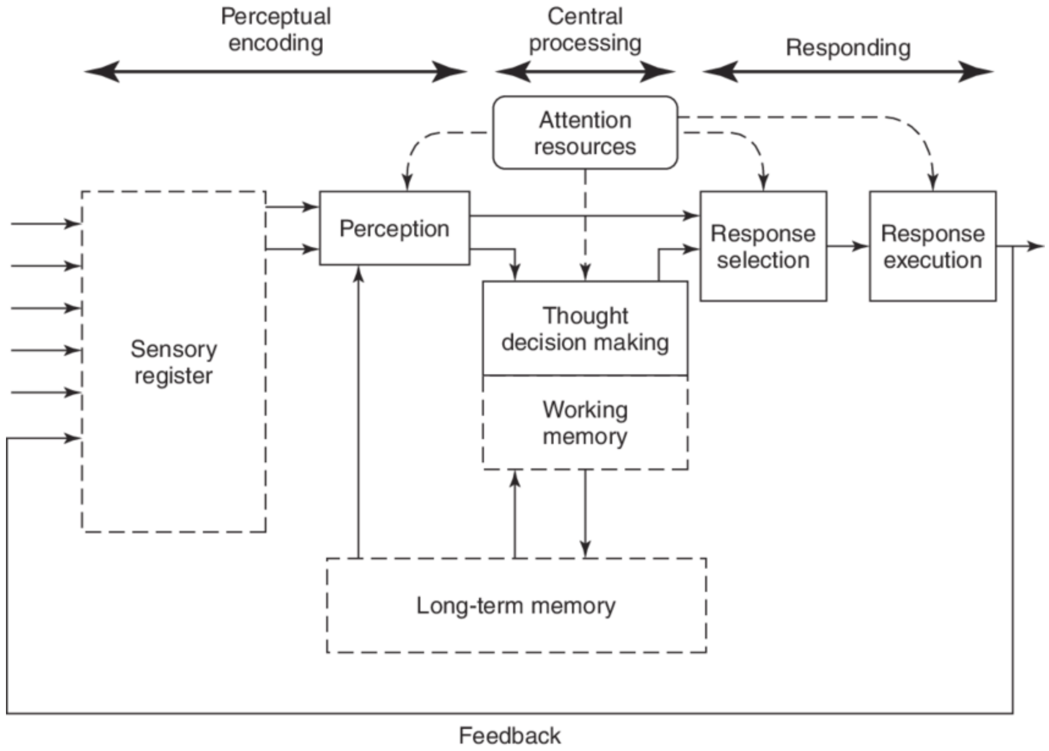

Figure 4. Wickens information processing model.
Source: Wickens et al. (2003).

In keeping with the scope of the thesis, we focus on the response selection of the model but will briefly touch on the areas of perception and decision making as needed. We are trying to understand if the observed responses are instinctual, or not, and if some type of conditioning, due to training, causes them.

2. Perception

Perception is drawing meaning from information received from our senses (Wickens et al. 2003). For this research, perception will only be in the form of visual perception. Perception requires visual attention. Visual attention is required to conduct visual searching. A visual search is any task in which we use our eyes to scan the environment to find the desired object. This concept is easy to understand by supplying examples. For example, searching for car keys, looking for certain types of produce at the grocery store, and even the children's game Where's Waldo are all types of a visual search (Dodd and Flowers 2012). Our attention can be on several different things at one time (Kahneman 1973). In the military it is necessary and essential to have situational awareness (SA); this comes from maintaining a list of present, past and possible future events on the field of battle along with keeping track of friendly and enemy forces (Livingston et al., 2011). SA is not possible if attention is focused on just one thing.

3. Response Selection

a. Conditioned Behavior vs. Institutional Behavior

Conditioning is a generic term used for a set of empirical concepts that specify the conditions that exist when associative learning takes place; conditioning leads to conditioned behavior. Most often conditioned behavior is divided into two categories: classical and operant (Reber, 2009).

Classical conditioning, also called Pavlovian conditioning, is when a "hard-wired" reflex, such as a dog salivating when it sees food, goes from an unconditioned stimulus (US) / unconditioned response (UR) to a conditioned stimulus (CS) / conditioned response (CR). In Pavlov's case it was U.S. (food) / UR (salivate) to CS (bell) / CR (salivate) (McLeod, 2018). Classical conditioning responses are involuntary, like blinking, or reflexive, like pain. The role of the learner is passive for classical conditioning.

With operant conditioning, the role of the learner is active, the nature of the response is voluntary, and reinforcement (positive or negative) is added to the learned behavior. In other words, the behavior that is being taught is tied to some type of reinforcement. This reinforcement is not in terms of good or bad; it is merely positive or negative. Operant conditioning was first illustrated in 1938 by B.F. Skinner with his experiment with caged rats. The rats were given food if they pressed a lever in the cage. At first, the rats hit it by accident but then over time, the rats learned that if they hit the lever, they would get food (Psychologist World, 2015). Operant conditioning is similar to military training in the case that the learner is in an active role and reinforcement is always a factor.

Institutional behaviors are similar to the conditioned behaviors but originate with the institution instead of the individual. For institutional behavior to take hold, an individual has to belong to a specific group that has deep-rooted beliefs, and membership in such instills these behaviors to their members. Examples of institutional behaviors can be seen in universities, large corporations, government, and the military (Floyd, 1933).

There is no secret that military members are conditioned both physically and psychologically. Behavioral psychology plays a vital role in training a person to follow orders and, when necessary, take another person's life (Grossman 2009; McKinnie 2016). The military uses a form of operant and institutional conditioning to transform an average civilian into a functioning member of their respective branch of service. No matter how short or long the individual remains in service, the conditioning received remains (Murray, Grossman, and Kentridge 2000).

A study conducted by Robinson (1933), in which observed data was collected on people entering museums, concluded that people have a bias to turn right upon entering a structure. Building from Robinson's study, Scharine and McBeath (2002) conducted an experiment in which they believed driving behavior and dominant hand played a role in which way a person would favor. Results from their study showed that right-handed people and those who learned to drive on the right side of the road favored moving to the right. Their findings were not significant relating to the participants' dominant eye or reading direction of their primary written language. It was noted that their sample size of right-to-left readers was too small to be conclusive. The participants that took part in Scharine and McBeath's research were identified as civilian college students; it is unknown if any of the participants were current or formal military. This study focuses on just the military population with regards to this behavior to favor left or right. This insight is valuable and could play a role with regards to the placement and identification of objects within an XR training or operational scenario.

b. Instinct

Some evolutionary psychologists would say that human instincts have evolved as humans moved from living in caves and having to be hunters and gathers, to the modern world we live in now (Pianka, 2012). Charles Darwin thought of instincts "as complex behavior patterns, unlearned and yet adaptive" (Ghiselin, 1973, p. 966). Psychologists have agreed that primary instincts come from one of three groups: self-preservation, sexual, and social (Riso and Hudson 1999). For this thesis, we looked at instinct from the self-preservation standpoint, thus examining if our hunter-gather instinct may lead us to first identify and interact with things that are outside of normal first. If something changes in our environment, is that the thing we attend to first? Self-preservation is essential to the military because, during combat, we are trained to identify and engage the enemy in order to control or eliminate them. The idea of providing enhanced information in a visual form to soldiers is not new but has the potential to distract them from real or more severe threats. Previously, digital information was limited to a vehicle or command post. Today we are poised to provide near real-time visual data to the individual soldier on the battlefield. Given what we know about instinct, it is vital to investigate the effects of integrating AR into an operational environment to determine the effects on individual and collective human actions.

III. METHODOLOGY

A. PARTICIPANTS

The population of interest in this study were military members of various ages and times in service. A total of 62 participants from the Defense Language Institute (DLI) in Monterey California volunteered to take part in this study. Of the 62 participants, 42 (68%) were male, and 20 (32%) were female. All the participants were U.S. Air Force military members.

B. STUDY DESIGN

The experiment was a between-subject design, with the participants performing a search task. The independent variables (IV) for this experiment were the placement of the real and rendered objects within the environment. The dependent variables (DV) were:

1. visual attending: left vs. right / right vs. left
2. room scan: yes / no
3. object choice: which object the participant move towards first (real / rendered)
4. time to complete: (in seconds) time to move toward an object

(see Figure 5 for data collection breakdown)

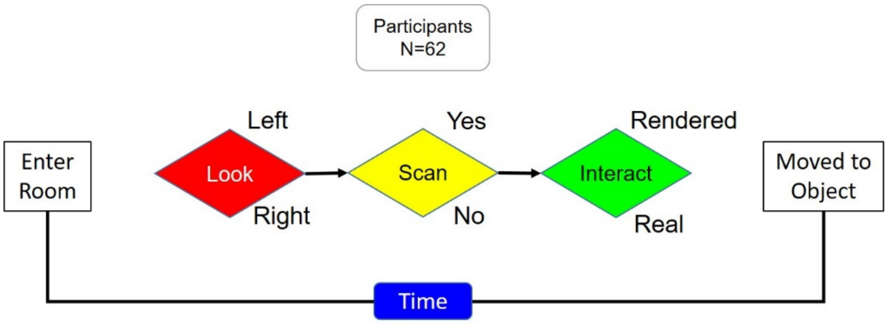

Figure 5. Data collection breakdown

Using a power calculation (see Appendix D for calculation), it was determined that 50 - 100 participants would be needed to have meaningful statistical results. To minimize the chance of carryover effect, each participant only took part in one data collection session. The experiment was conducted in a controlled laboratory setting. The room designed for this experiment had the doorway in the middle of one wall. We placed the objects along that wall, on opposite sides of the doorway (see Figure 6).

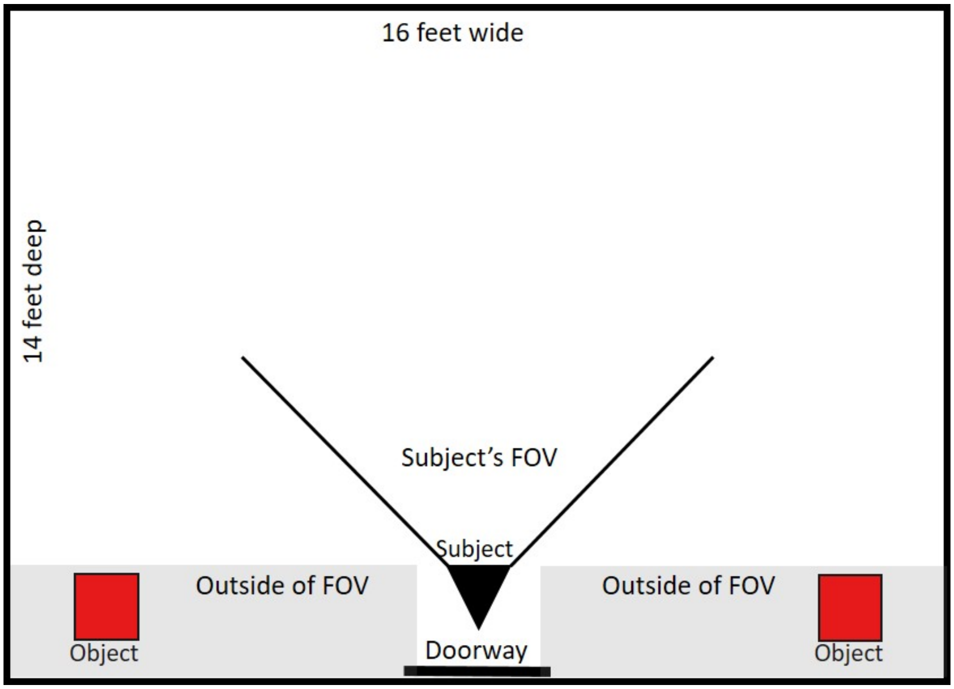

Figure 6. Real vs. rendered room setup

The real and rendered objects in the room were brown cardboard boxes of similar size, shape, and design. The virtual environment (VE) was developed using the Unity game engine. We placed the real and rendered objects in a sterile room setting that contained nothing other than the real box. These parameters allowed for clear observation of the participants throughout the experiment. The distance of the real and rendered boxes from the doorway and the limited field of view (FOV) of the Magic Leap One (ML1) created an environment where both objects (real and rendered) were outside of the FOV of the participants. Figure 7 shows the FOV with and without the ML1 as a participant enters the doorway; it is important to note that the view through the ML1 limits the participant's ability to see the corners of the room, due to the narrow FOV.

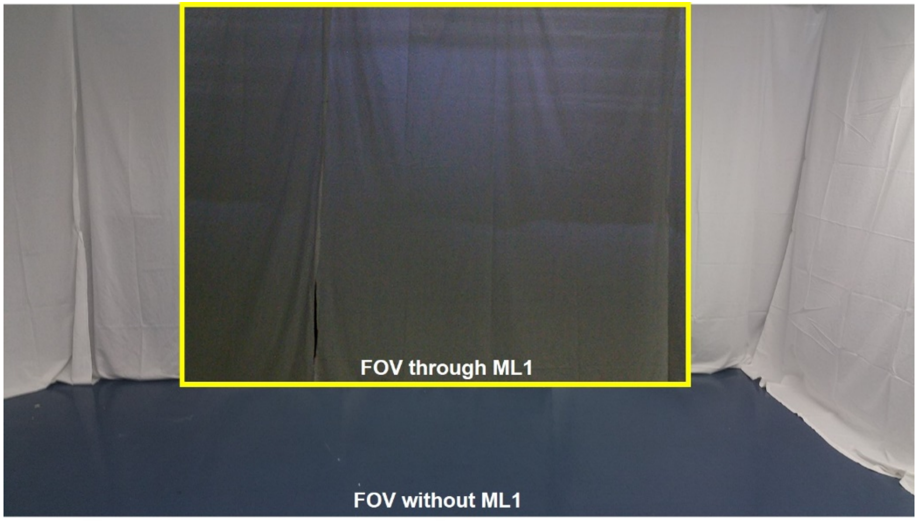

Figure 7. View through doorway with and without Magic Leap One

With the objects placed outside of the FOV of the participants, they had to turn their heads in order to view the objects. We designed the setting in this manner to provide us with insight into the instinct of the participants when all other distractions have been eliminated. The participants also took part in a pre-test and post-test questionnaire.

C. INSTRUMENTS

1. Questionnaires

Two questionnaires were developed for this experiment, a pre-test and post-test.

The pre-test questionnaire allowed us to gather the demographics of our participants. The pre-test questionnaire included 10 questions capturing the following data:

1. Gender: male/female
2. Age (years)
3. Dominant hand: right/left handed

4. Corrective lenses (yes/no)
5. English a second language (yes/no)
6. Years of military service (years/months)
7. Experience with search tasks (yes/no)
8. Experience with augmented reality (yes/no)
9. Likert scale 1 (hate it)- 5 (love it) attitude toward technology
10. Hours of sleep

The post-test questionnaire allowed for improvement and identification of unforeseen issues with the experiment, along with confirmation of data collected from researcher. The post-test questionnaire included the following nine questions:

1. Have you ever received any training, or had experience in how to search or search patterns? If yes, what type and when?
2. Which object did you notice FIRST when you entered the room?
3. Which object did you FIRST interact with?
4. Please explain why you think you picked that object first.
5. Given a choice would you rather interact with all real objects or all rendered objects?
6. Given the task we asked you to conduct, what did you dislike about the environment, and what did you like?
7. Do you think AR could be used for more than just training?
8. How do you think AR could be improved?
9. Please provide any other questions, comments or concerns about anything dealing with the experiment.

2. Equipment

The ML1 AR-HMD device is used to render the virtual environment (VE) over the real world. Figure 8 shows the ML1 AR-HMD device that was used for this experiment.

Figure 8. Magic Leap One AR-HMD

The software used on the ML1 was operating system (OS) version 0.95.2. The ML1 was chosen due to its more extensive field of view (FOV) and faster processing speed over similar competitors' models, namely Microsoft HoloLens. The ML1 has a horizontal FOV of 40 degrees, a vertical FOV of 30 degrees, and a diagonal FOV of 50 degrees, compared to the HoloLens horizontal FOV of 30 degrees and a vertical FOV of 17.5 degrees. This gives the ML1 approximately a 45% larger FOV than that of the of HoloLens (see Figure 9).

Figure 9. FOV Magic Leap vs. HoloLens1

The Unity game engine was used to create the VE. Unity is a free and powerful game engine used to develop environments for personal, educational, and professional reasons. The Unity version used in this research was 2019.1.0f2. The VE allowed for the creation and placement of the rendered objects in the real world. (See Appendix A for setup and codes used to allow ML1 to work with Unity.) Along with the Unity application, Unity API Documentation version 0.20.0 and Magic Leap Unity Package 0.20.2 are needed for ML1 and Unity to communicate and function properly. We used Visual Studio 2017 extension 1.0.190301 and Visual Studio code extension 0.9.8 to create and adjust the C-sharp code needed to manipulate the object in the VE.

Unity was run on an Alienware computer that met or exceeded the minimum systems requirements outlined by Unity. These minimum requirements are OS Windows 7 SP1+, 8, 10, 64-bit versions only; Mac OS 10.12+, central processing unit (CPU) with SSE2 (Streaming SIMD (Single Instructions, Multiple Data) Extensions 2) instructions set support and graphics processing unit (GPU) graphics card with DX10 (shader model 4.0) capabilities.

A medium-sized, heavy-duty, cardboard “moving” box, 18 x 18 x 16 inches, was purchased from Lowe’s and used for the real object. The rendered object was approximately the same size and color as the real box (see Figure 10). The size of the rendered object was determined by placing the rendered object over top of the real object. From there, the size was adjusted until no over or underlap was detected. It is a very close approximation of the real object.

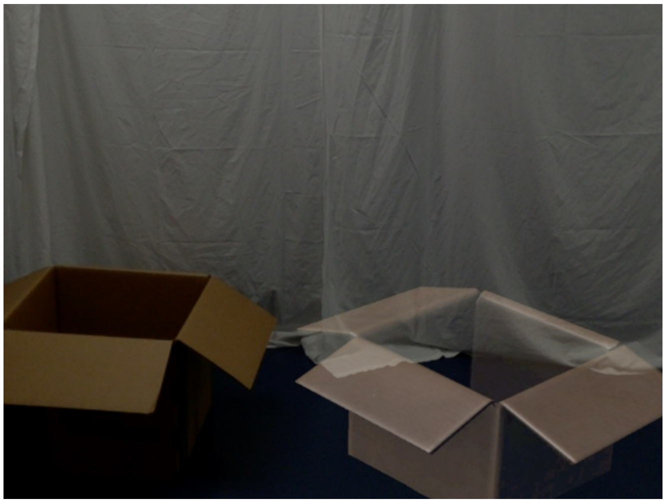

Figure 10. Real on left and rendered on right

A rubber duck (see Figure 11) was used as the object the participants were told to find within the environment.

Figure 11. The rubber duck

Cloth sheets were used as the experiment room’s walls. The room was 16 x 14 x 7.25 feet. Any gaps in the sheets were held closed with safety pins. An opening, simulating a doorway, was made so that it would open to the middle of the room. There was a slight gap for the doorway and two signs labeled “Door” to allow the participants to see the door’s location. This gap did not permit the participants to see the inside of the room before entering (see Figure 12).

Figure 12. View of doorway entrance from outside of experiment room

D. PROCEDURES

Both the NPS and DLI in Monterey, California, Human Research Protection Program & Institutional Review Boards reviewed and approved the study design (see Appendix B for approvals). This process required the review of the thesis proposal, all questionnaires that the participants would complete, the data to be collected, data collection sheet, recruitment e-mail, recruitment script, procedures script, conflict of interest forms, scientific review form, and applications for both NPS and DLI. All members of the research team were required to have ethics training.

The experiment took place at DLI Monterey, CA. Data collection took place on two different days, about a month apart. Location for the experiment was selected due to close proximity to the participant pool. In order to ensure that the ML1 device was calibrated and the objects could be placed in the environment without issues, the experiment room was set up the day prior to execution. The room allowed the cloth sheets to hang from the ceiling. Once all sheets were in place, the ML1 device was turned on inside the room. The ML1 device then scanned the inside of the room – this is an automatic function every time it is booted up – which allows spatial mapping of the environment, walls, floors, and ceiling, and any items within the area. Two conditions were used during the experiment:

1. real object on the right and rendered object on the left
2. real object on the left and rendered on the right

Participants were randomly assigned to room layout groups.

When the participants arrived, the researcher welcomed them, read the informed consent form to them, and had them sign a copy of the form. They were given scripted directions (see Appendix C) on the tasks they were going to take part in, proper wear of the ML1 and a pre-test questionnaire.

Once complete with the pre-test questionnaire, each participant was given at least five minutes to familiarize themselves with the AR device. At no time was any participant given longer than 10 minutes to familiarize themselves with the device. The purpose of limiting the familiarization time was to reduce the risk of cyber or motion sickness symptoms. This familiarization consisted of using ML1 application Create (see Figures 13 and 14).

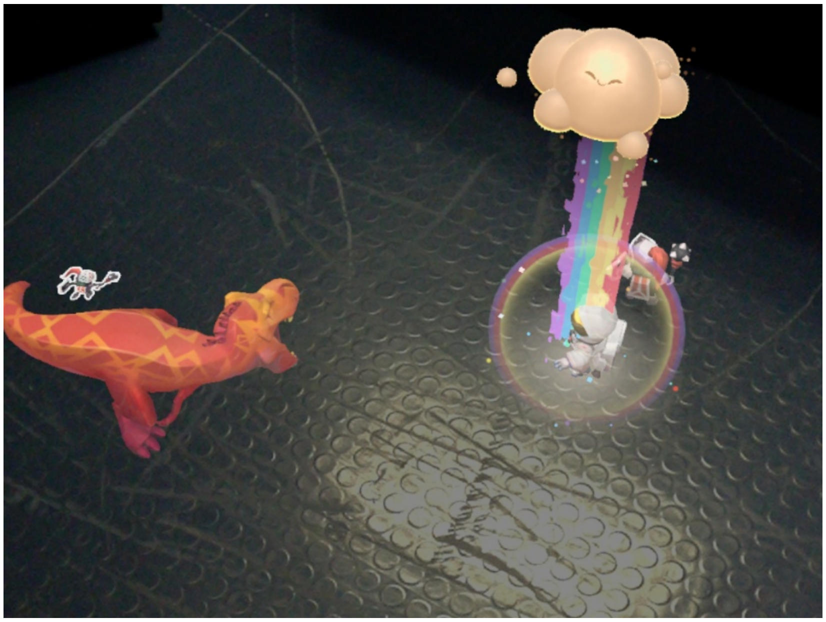

Figure 13. Magic Leap Create App used for familiarization

The Create application allowed users to see what rendered objects looked like once overlaid on the real world and how to interact with these objects. During this time, participants could ask questions or express any concerns they might have.

Figure 14. Another image of Magic Leap Create

After completing the pre-test and familiarization, the participants moved to a staging area for the search task. They were instructed to put on the ML1 device and look at the ML1 remote control located on a nearby desk (see Figure 15). This was done to ensure that they saw a rendered remote over top of the real remote. This served two purposes: 1) to confirm that the Unity VE was still running, and 2) to show the participants how a rendered object will look inside the environment.

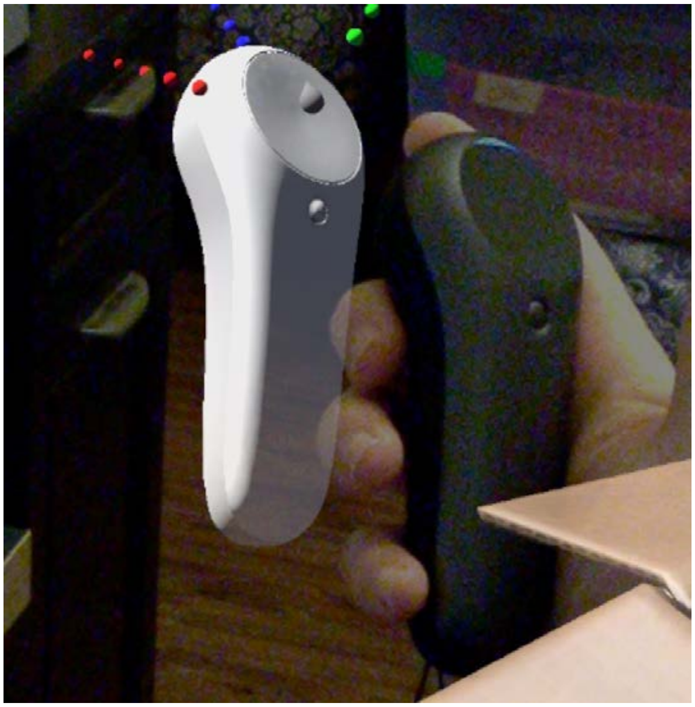

Figure 15. Rendered [L] and real [R] remote

The participants were again given directions that they were about to conduct a search task, that they were looking for a rendered object (rubber duck, see Figure 11) which could be anywhere in the room, and that it could be inside a real or rendered object. Once the participant acknowledged they could see the rendered remote and understood the directions, they moved to the doorway of the experimental room.

Time began once the participant opened the doorway. A total of two minutes was given to each participant to execute the search task. The experiment was complete, and the time stopped, when the participant moved toward an object, either real or rendered. They were then asked if they saw both the real and rendered object in the room. They were then told that there was no rubber duck in the room and that the true nature of the experiment was to see if humans have a natural instinct to favor real over rendered objects in an XR environment. They were asked not to discuss the experiment with anyone waiting to conduct the experiment. They were then given a post-test questionnaire and thanked for their time (see Figure 16).

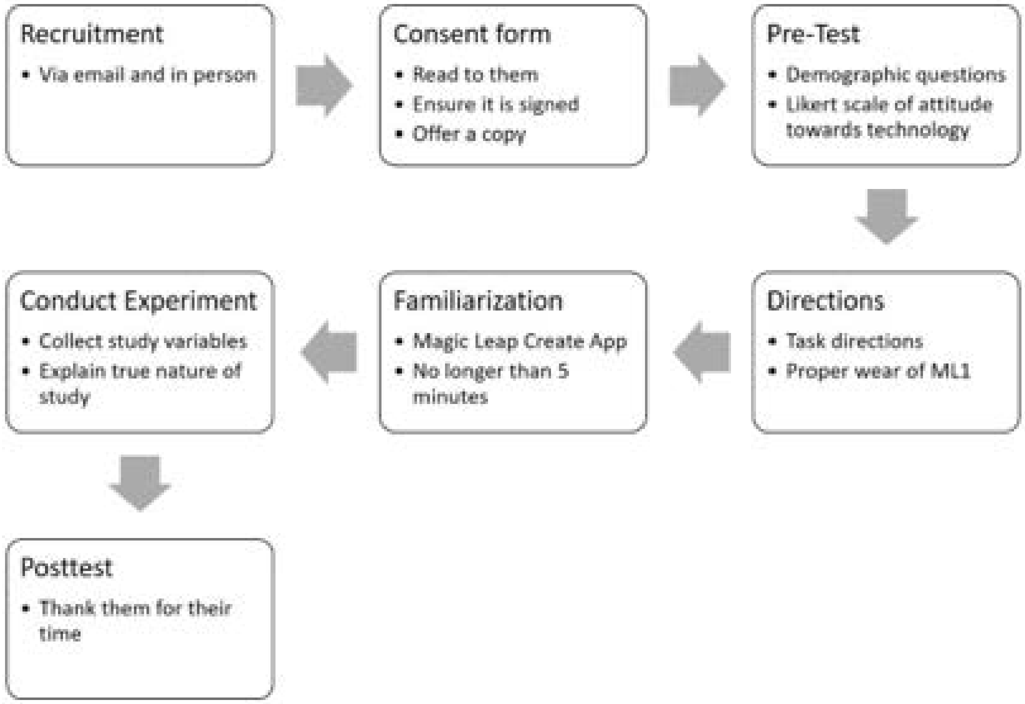

Figure 16. Process flow of experiment

E. ANALYTICAL ASSESSMENT

1. Data Preparation Procedures

All the data collected during the study were found to be useable without the need of further reduction or preparation.

2. Analysis Roadmap

Statistical analysis was conducted with JMP 14.0.0, and Excel 2016. A one-proportioned Z-test, a two-proportioned Z-test and a two-sample T-test were used to analyze the data. If the conditions and assumptions were not met for these tests, then the Wilcoxon signed-rank or the Chi squared test was used. All analyses that required a significance level, used a 0.05 alpha unless otherwise stated. Data are presented as mean (M), standard deviation (SD) or median (MD), as needed.

The expected model of participant behavior in the VE is that the participant enters the room looks left, then scans the room, and finally moves to the real object to conduct the search task.

First, we assessed the demographic attributes of our participants, followed by a detailed description of the behaviors of our participants in the AR. Next, we conducted a multiple regression analysis to identify the predictor factors of the four dependent variables (DV): visual attending, room scan, object choice, and time to complete the task. We did this because, according to Field, "Regression analysis is a way of predicting an outcome variable from … several predictor variables (multiple regression)" (2009, p. 198). When the first model for each DV was statistically significant, we used the backward reduction method. With the backward method all potential predictor factors are placed in the model, and from the resulting calculation, it is determined if the predictor factors meet the significance level for removal. Then the model is reassessed with the remaining factors (Field, 2009). The initial logistic models of visual attending, room scan, and object choice included five variables; four potential predictor factors (gender, years of service [<3 versus >6], experience with search tasks, and experience with AR), and one confounding factor (room condition). The initial regression model of the time to complete the task included seven variables; six potential predictor factors (gender, years of service [<3 versus >6], experience with search tasks, experience with AR, room scan, visual attending), and one confounding factor (room condition).

IV. RESULTS

A. DEMOGRAPHICS

Participants' ages ranged from 18 to 42 years of age (MD = 19). The time in service ranged from three months to 16 years (MD = 1). Of the participants, nine (15%) were left-handed and 53 (85%) were right-handed. Corrective lenses were worn by 27 (44%) of the participants. We had 55 (89%) participants who were native English speaking with seven (11%) who had English as a second language. Only 17 (27%) participants stated they had experience with search type tasks and 45 (73%) did not have any experience with search tasks. When asked about experience with AR, 44 (71%) participants stated they had no experience; 18 (29%) stated that they did. Participants' attitude towards technology was positive, with five (8%) reporting they like technology, 22 (35%) reporting they like / love technology, and 35 (57%) reporting they love technology. The participants' average nightly sleep ranged from five to 12 hours the night prior to the experiment (MD = 7).

B. BEHAVIOR IN THE XR

We observed 40 (65%) participants visually attended to their left side first. Upon entering the room 45 (73%) participants scanned the room. Only eight (13%) participants interacted with the real object first. Time to complete ranged from 4.57 seconds to 34.28 seconds (MD = 11.0) (see Figure 17).

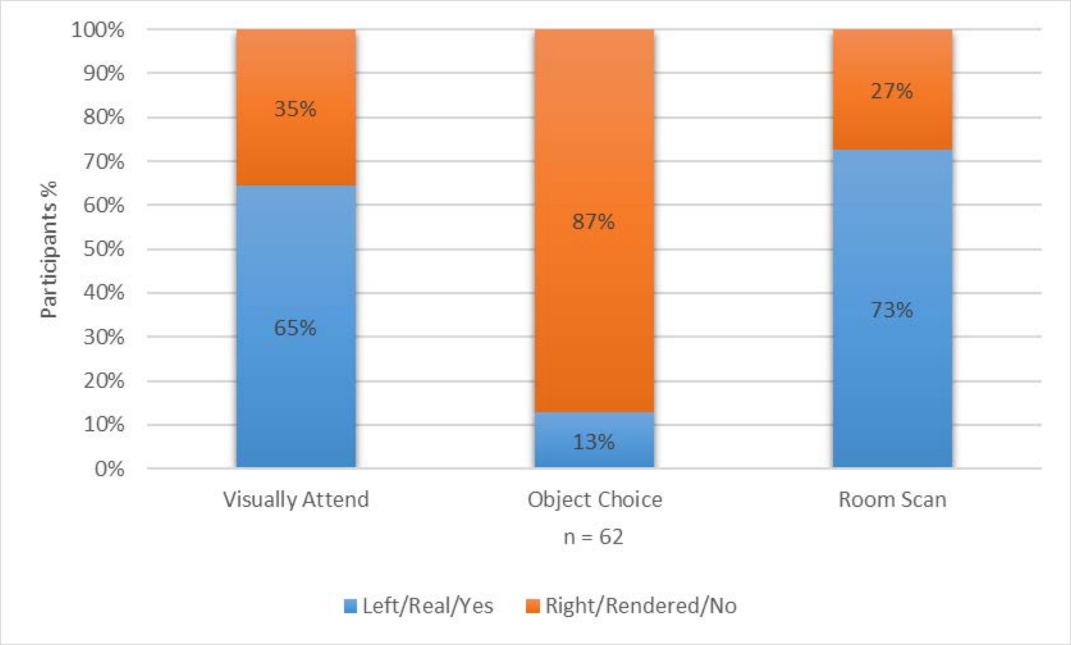

Figure 17. Observed behaviors in the XR

This experiment had two room conditions Condition One (C1) had the real box on the right side of the room and the rendered box on the left side, whereas Condition Two (C2) was the opposite. For C1, 19 (61%) participants visually attended their left side first, 23 (74%) scanned the room, five (16%) interacted with the real object and time to complete ranged from 5.16 seconds to 34.3 seconds (MD = 11.1). Likewise, for C2, 21 (68%) participants visually attended their left side first, 22 (71%) scanned the room, three (10%) interacted with the real object, and time to complete ranged from 4.57 seconds to 20.1 seconds (MD = 10.9) (see Figure 18).

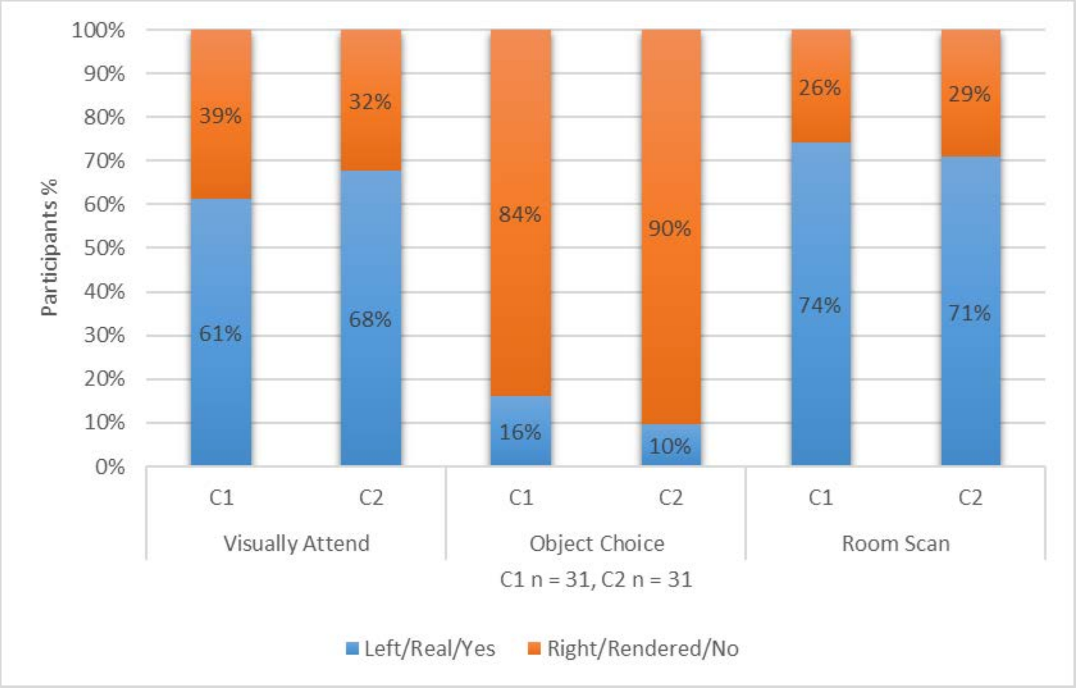

Figure 18. Observed behaviors by experimental condition

Overall, participant behavior while performing the search task in the XR is shown in Figure 19.

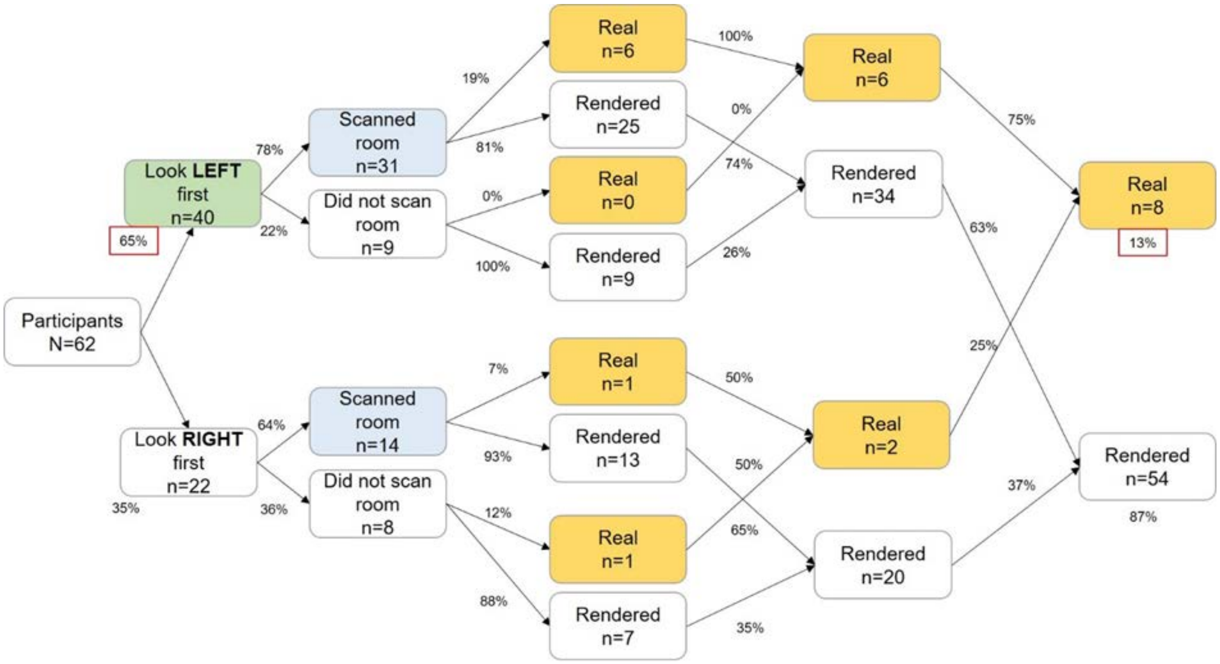

Figure 19. Overall behavior in the XR.

C. CORRELATION ANALYSIS

We conducted a pair-wise correlation analysis of the study variables: participant age, gender, dominant hand, English as a second language, use of corrective lenses, years of service (YoS), experience with search tasks, experience with AR, hours of sleep, visual attending, room scan, object choice, and time to complete. The levels of binary categorical variables were assigned a number to calculate the point-biserial correlation coefficient.

Results showed that age is correlated with YoS (Pearson’s $r = 0.97$, $p < 0.0001$), visual attending is correlated with age ($r = 0.27$, $p = 0.030$) and YoS ($r = 0.26$, $p = 0.040$). Gender is weakly correlated with time to complete the task ($r = -0.25$, $p = 0.050$). Also, object choice was weakly correlated with gender ($r = -0.25$, $p = 0.050$), and dominant hand ($r = -0.25$, $p = 0.050$). Detailed results are shown in Table 1.

Table 1. Correlation matrix using Pearson’s r

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]
[1] Age	1.00												
[2] Gender	0.14	1.00											
[3] Lenses	-0.34**	-0.23	1.00										
[4] English	0.01	-0.19	0.10	1.00									
[5] Handed	0.04	0.11	0.27*	0.00	1.00								
[6] Sleep	-0.05	0.09	-0.15	-0.17	-0.15	1.00							
[7] YoS	0.97***	0.10	-0.34**	-0.05	0.04	0.00	1.00						
[8] Exp Search	0.06	0.04	0.19	0.12	0.15	0.04	0.09	1.00					
[9] Exp AR	-0.12	0.14	-0.06	0.11	-0.04	0.05	-0.12	0.24	1.00				
[10] Scan	0.11	0.04	0.18	0.11	-0.05	-0.09	0.07	0.05	0.07	1.00			
[11] Visual	0.27*	-0.01	-0.03	-0.06	-0.11	-0.19	0.26*	0.15	-0.12	0.15	1.00		
[12] Time	0.20	-0.25	0.19	0.14	-0.21	-0.21	0.22	-0.11	0.14	0.21	0.13	1.00	
[13] Object	-0.01	-0.25	-0.14	0.01	-0.25*	0.03	0.02	-0.24	-0.03	0.13	0.08	0.08	1.00

“*” $p < 0.05$; “**” $p < 0.01$; “***” $p < 0.001$

D. ASSESSMENT OF THE STUDY HYPOTHESES

Our first hypothesis was that military members will look left first. Results showed that 40 (65%) participants attended to their left side first upon entering the room. This finding differs from the null hypothesis, that 50% of the participants will look left first, at a statistically significant level (one-sided binomial test, $p = 0.015$).

The second hypothesis was that humans in an XR environment will favor real objects over rendered objects. Our data showed that only eight (13%) participants interacted with the real object first. This finding differs from the null hypothesis at a statistically significant level (one-sided binomial test, $p < 0.001$).

E. PREDICTOR FACTORS OF DEPENDENT VARIABLES

1. Visual Attending

The multiple logistic model of visual attending included five variables: four potential predictor factors (gender, years of service [<3 versus >6], experience with search tasks, and experience with AR), and one confounding factor (room condition). Results showed that the model for visual attending was not statistically significant ($\chi^2(5) = 5.93$, p = 0.313, Nagelkerke $R^2 = 0.125$). Detailed results are shown in Table 2.

Table 2. Multiple logistic regression results for visual attending

Predictor factor	b	b SE	χ^2	p-value	95% CI
Room condition (C1)	-0.033	0.295	0.01	0.912	-0.614 – 0.553
Gender (female)	0.021	0.304	0.0	0.945	-0.573 – 0.633
Years of service (<3)	-0.556	0.359	2.40	0.121	-1.35 – 0.101
Experience with search tasks (no)	-0.437	0.352	1.55	0.213	-1.19 – 0.20
Experience with AR (no)	0.336	0.333	1.02	0.313	-0.314 – 1.01

SE: Standard Error

CI: Confidence interval

2. Room Scan

The multiple logistic model of room scan included five variables: four potential predictor factors (gender, years of service [<3 versus >6], experience with search tasks, and experience with AR) and one confounding factor (room condition). Results showed that model for room scan was not statistically significant ($\chi^2(5) = 0.737$, p = 0.981, Nagelkerke $R^2 = 0.017$). Detailed results are shown in Table 3.

Table 3. Multiple logistic regression results for room scan

Predictor factor	b	b SE	χ^2	p-value	95% CI
Room condition (C1)	-0.072	0.301	0.06	0.811	0.674 – 0.522
Gender (female)	0.078	0.309	0.06	0.801	-0.549 – 0.679
Years of service (<3)	0.140	0.335	0.18	0.676	-0.492 – 0.849
Experience with search tasks (no)	0.093	0.346	0.07	0.789	-0.565 – 0.821
Experience with AR (no)	0.152	0.356	0.18	0.669	-0.527 – 0.896

SE: Standard Error

CI: Confidence interval

3. Object Choice

The initial logistic model of object choice included five variables, four potential predictor factors (gender, years of service [<3 versus >6], experience with search tasks, and experience with AR) and one confounding factor (room condition). The initial model for object choice was statistically significant ($\chi^2(5) = 11.1$, $p = 0.050$, Nagelkerke $R^2 = 0.304$), with gender ($p = 0.037$) and experience with search tasks ($p = 0.010$) being the statistically significant predictor factors. Based on the abovementioned results, we omitted the room condition. That led to a statistically significant model ($\chi^2(4) = 11.0$, $p = 0.027$, Nagelkerke $R^2 = 0.303$), with gender ($p = 0.035$) and experience with search tasks ($p = 0.009$) being the statistically significant predictor factors. Lastly, we omitted the years of service and experience with augmented reality and developed the third model ($\chi^2(2) = 9.08$, $p = 0.011$, Nagelkerke $R^2 = 0.254$). Experience with search tasks remained statistically significant ($p = 0.019$), whereas gender showed a trend towards statistical significance ($p = 0.061$). Therefore, *gender and experience with search tasks were consistently associated with object choice*. Specifically, *our results suggested that males and participants experienced with search tasks tended to interact with the rendered object more than females or participants without experience with search tasks*. Detailed results are shown in Table 4.

Table 4. Multiple logistic regression results for object choice

	Model 1		Model 2		Model 3	
Intercept	χ^2	p-value	χ^2	p-value	χ^2	p-value
Room condition	0.040	0.842	-	-	-	-
Gender	4.36	0.037	4.45	0.035	5.51	0.019
Years of service	1.46	0.227	1.63	0.202	-	-
Experience with search tasks	6.60	0.010	6.82	0.009	3.52	0.061
Experience with AR	0.480	0.488	0.662	0.416	-	-

Results refer to the Likelihood Ration tests for the effects

4. Time to Complete the Task

The initial multiple regression model of the time to complete the task included seven variables; six potential predictor factors (gender, years of service [<3 versus >6], experience with search tasks, and experience with AR, room scan, visual attending) and one confounding factor (room condition). The initial model for time to complete was statistically significant ($F(7,54) = 2.75$, $p = 0.016$, adjusted $R^2 = 0.167$), with gender (p =

0.020) and years of service (p = 0.008) being the statistically significant predictor factors. Based on the abovementioned results, we omitted the room condition. That led to a statistically significant model (F (6,55) = 3.26, p = 0.008, adjusted $R^2 = 0.182$), with gender (p = 0.019) and years of service (p = 0.008) being the statistically significant predictor factors. Lastly, we omitted visually attend and experience with augmented reality and developed the third model (F (4,57) = 4.23, p = 0.005, adjusted $R^2 = 0.175$). Gender (p = 0.030) and years of service (p = 0.008) remained statistically significant, whereas conduct room scan showed a trend towards statistical significance (p = 0.067). Therefore, *gender and years of service were consistently associated with time to complete*. Specifically, *our results suggested that males, participants with less than three years in service and participants who did not conduct a room scan tended to complete the task faster than females or participants with greater than three years in service or participants who conducted a room scan*. Detailed results are shown in Table 5.

Table 5. Multiple linear regression results for time to complete

	Model 1		Model 2		Model 3	
Intercept	t	p-value	t	p-value	t	p-value
Room condition (C1)	-0.20	0.839	-	-	-	-
Gender (female)	2.40	0.020	2.43	0.018	2.23	0.030
Years of service (<3)	-2.76	0.008	-2.78	0.008	-2.74	0.008
Experience with search tasks (no)	1.74	0.087	1.75	0.086	1.37	0.176
Experience with AR (no)	-1.55	0.128	-1.56	0.125	-	-
Visually attend (left)	0.38	0.704	0.39	0.699	-	-
Room Scan (no)	-1.69	0.097	-1.70	0.095	-1.87	0.067
Overall Model p-value	0.016		0.008		0.005	
Adjusted R^2	0.167		0.182		0.175	

F. SUMMARY

Upon testing our hypothesis in regards to visual attending we did find it to be statistically significant (one-sided binomial test, 0.015), but our multiple logistic regression model did not reveal any statistically significant potential predictor factors.

Our hypothesis with regards to object choice was also found to be statistically significant (one-sided binomial test, $p < .0001$), and the multiple logistic regression model showed that gender and experience with search tasks were consistently associated with object choice.

A multiple regression model into time to complete the task revealed that gender and years of service were consistently associated with time to complete.

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V. DISCUSSION

A. IMPLICATIONS

As XR technology advances it is important for the Army and the DoD to understand that just because a technology holds promise to provide an edge on the battlefield does not mean that it will or that it will not actually create a hazard. This research had two goals. The first goal was to investigate potential human bias or preference of engagement with real and rendered objects while in an XR environment. The second goal was to determine if conditioned behavior exists within the military that might influence human behavior in an XR environment.

Our experiment with 62 Airmen showed that there was statistical significance with regards to human preference of object choice ($p < 0.001$); we revealed that 87% of our participants chose to interact with rendered objects first over real ones. Further investigation into potential predictor factors reveled that *gender* and *experience with search tasks* were consistently associated with object choice. Specifically, our results suggest that *males and participants experienced with search tasks* tend to interact with the *rendered object* more than females or participants without experience with search tasks.

With regards to military members' visual attending, specifically the behavior to move or look to their left first, our study showed that 65% of our participants demonstrated the behavior to look left first. Our results differ from those of *Scharine and McBeath (2002), in which they found people who learn to drive on the right side of the road, or who are right-handed, favor looking or moving to the right first*. Our data suggest that *military members might differ from the general public with regards to this behavior*. We were unsuccessful in determining potential factors related to this behavior. However; there was a slight trend with years of service (> 6) and visual attending but it was not statistically significant within our models.

B. LIMITATIONS

Hardware-related issues presented the most significant limitation during our experiment. The experimental room setup was chosen because it allowed us to see clearly which object the participants chose, real or rendered. We did not anticipate the ML1 would have issues of spatial mapping and recognizing the experimental room; we believe these issues were caused by the conditions that the color contrast with the room was not significantly different, the room was empty during spatial mapping, and that the lighting of the room over which we had no control. The room was entirely white – walls (sheets), floor, and ceiling. When scanning the room, it was empty. The lighting in the space used for the experiment was fluorescent ceiling lighting, and the room had a low ceiling. This spatial mapping issue caused delays in conducting the experiment due to several factors. At times the issue would cause the walls to not be recognized, and the rendered object could be seen before entering the room. Other times it would move the rendered object before starting the experiment. Anytime this would occur, the application would have to be stopped and restarted, or in some cases, the entire ML1 had to be rebooted.

Another limitation concerning the hardware was when a participant would remove the device, the ML1 would go into sleep mode. When placing the ML1 back on, the headset would need to recalibrate and would cause issues with the application. These issues include moving the placement of the object, or not rendering the object at all.

Issues with the object placement and the see-through walls required the researcher to establish the room condition for each participant conducting the task. To avoid the headset issue, the researcher had to wear the ML1, maintaining headset alignment, and then pass it over to the participant before they could begin the experiment.

Since this experiment needed a larger sample size, we recruited from DLI in Monterey, CA. The pool of volunteers were all Airmen that had either completed training at DLI or were waiting to begin training at DLI. The access to these participants was limited due to their additional duties, which caused the experiment to be conducted in one day using this pool of participants. We broke the volunteers into groups of 10; it took approximately 45–60 minutes for all 10 participants to complete the experiment. Both the pre-test and post-test questionnaires relied on the participants' understanding of the question and their subjective honest answers. The participants we obtained for this study were all enlisted members of the U.S. Air Force. Our study called for military members, but having only one branch of the services represented was a limitation of our study.

VI. CONCLUSION

Overall, our results show that our participants tended to look left first (65% of the participants) and chose to interact with the rendered object first (87% of the participants). With these two pieces of information, we now have better insight into how military members may basically behave while in an XR environment. This insight is essential. Military missions are made from a series of other simple and complex tasks. The DoD is moving fast to incorporate more AR/VR into training and operational environments by testing commercial off the shelf technologies in the field without first determining a baseline of expected behavior with the technologies. We feel that this gap in research may lead to severely negative consequences and are working to fill it. This thesis is the first step on a journey to help the DoD fully understand the positive and negative impacts of XR in the training and operational space.

A. FUTURE WORK

Future work on this line of research has already begun. Another NPS Master's student is preparing to replicate this study and examine if a modification to the fidelity of the rendered object changes the outcome of the object choice. The following additional modifications of the task are also being programed into further research:

- Change the size of the object. One condition could be larger real object and smaller rendered object, then opposite for the second condition.
- Change the color of the objects. Consider brightly colored objects verses dull colored objects.
- Add more than two objects (one real, one rendered) to the room.
- Adjust the scenario from a search task to a room clearing task; scale the complexity of activity from basic to complex.
- Add stress to the VE by coding in a count-down timer that displays in the AR-HMD.

Further investigation into the conditioned behavior of visual attending should include the following:

- Participants that are not U.S. natives. Countries where driving on the right side of the road like England, Australia, New Zealand and Japan have several pedestrian signs that say “look right.”
- Include members from countries where they have been taught to read right to left.
- Larger number of participants to investigate handedness and its impact on moving left or right.
- Seek participants from multiple branches of the U.S. armed forces.
- Include all ranks enlisted and officers to determine if there is a difference based on factors unique to these two populations (e.g., education, time in service, etc.).

B. RECOMMENDATIONS

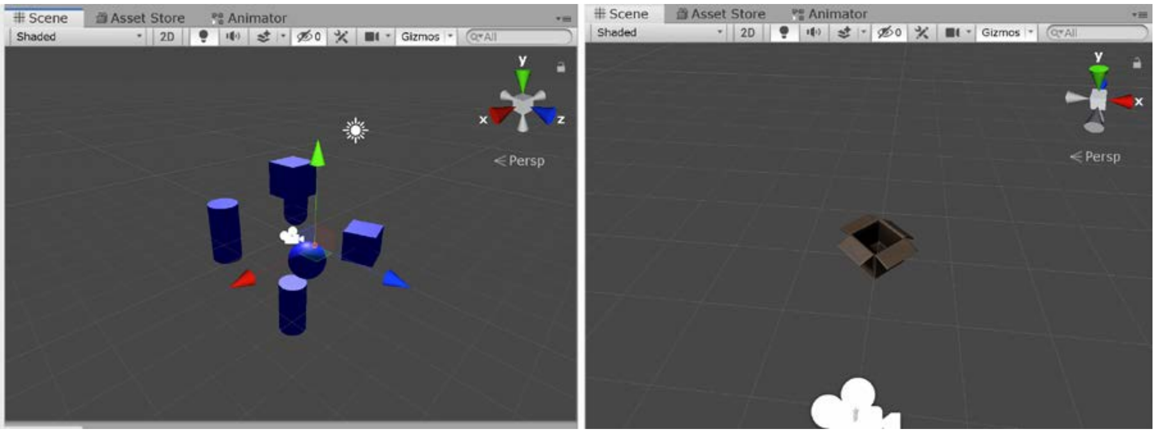
The practical impact that humans have a tendency to interact with a rendered object first while in an XR environment could have catastrophic results if applied to operational applications. Further investigation into the phenomenon is required. This line of research should be continued and modifications made to the experiment in an attempt to normalize the results with regard to object choice.

APPENDIX A. MAGIC LEAP SETUP AND CODE

Setup Magic Leap by completing the following steps.

1. Install Magic Leap package manager
2. Install required packages from Magic Leap package manager: Lumin SDK, C API Documentation, power and thermal profiler, Visual Studio code extension, Visual Studio 2017 extension, Unity API documentation, Unity editor, Magic Leap Unity package.
3. Configure new Unity project following directions provided at https://circuitstream.com/deploy-magic-leap-one-unity/ https://creator.magicleap.com/learn/guides/unity-setup
4. Complete "Hello Cube" tutorial follow direction provided at https://creator.magicleap.com/learn/guides/gsg-create-your-first-unity-app

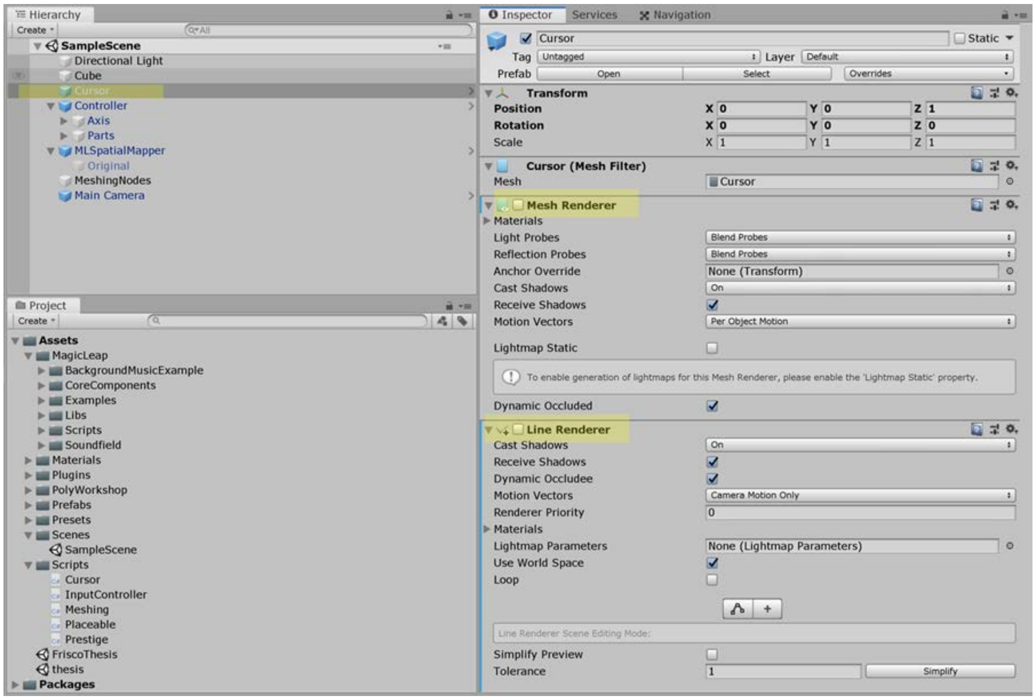
The VE for the experiment was a modified version of the "Object Picker" Untiy project which was developed by Rodney Degracia obtained from the following URL: https://github.com/magicallightandsound/ObjectPicker. The Degracia version had multiple objects in the Unity scene, we removed all but one object from the scene (see Figure 19). We then applied a free asset from the Unity store to the object (a cube) so that it would look like an open cardboard box. The free asset, "Cardboard Boxes Pack," was created by POLYWORKSHOP.



Degracia object picker scene on the left and our scene on the right.

Figure 20. Unity VE scene

No modification to the Degracia script code was conducted. It was necessary to eliminate the visual effect of a mesh for each object and a ray cast that would appear out of the ML1 remote. This was done by unselecting mesh renderer and line rendered under the curser object (see Figure 20).



☑ Cursor ☐ Static
Tag Untagged Layer Default

Transform

Position	X 0	Y 0	Z 1
Rotation	X 0	Y 0	Z 0
Scale	X 1	Y 1	Z 1

Cursor (Mesh Filter)
Mesh Cursor

☐ **Mesh Renderer**
Materials
Light Probes Blend Probes
Reflection Probes Blend Probes
Anchor Override None (Transform)
Cast Shadows On
Receive Shadows ☑
Motion Vectors Per Object Motion
Lightmap Static ☐
To enable generation of lightmaps for this Mesh Renderer, please enable the 'Lightmap Static' property.
Dynamic Occluded ☑

☐ **Line Renderer**
Cast Shadows On
Receive Shadows ☑
Dynamic Occludee ☑
Motion Vectors Camera Motion Only
Renderer Priority 0
Materials
Lightmap Parameters None (Lightmap Parameters)
Use World Space ☑
Loop ☐
Line Renderer Scene Editing Mode:
Simplify Preview ☐
Tolerance 1

Figure 21. Scene changes

Once our Unity application was complete we installed it onto the ML1 by following the directions previously provided for the “Hello Cube” tutorial.

Unity files for this study are located at https://gitlab.nps.edu/djfrisco/real-vs-rendered-in-xr for access please contact Jason Frisco at donald.j.frisco.mil@mail.mil or Glenn Hodges at gahodges1@nps.edu

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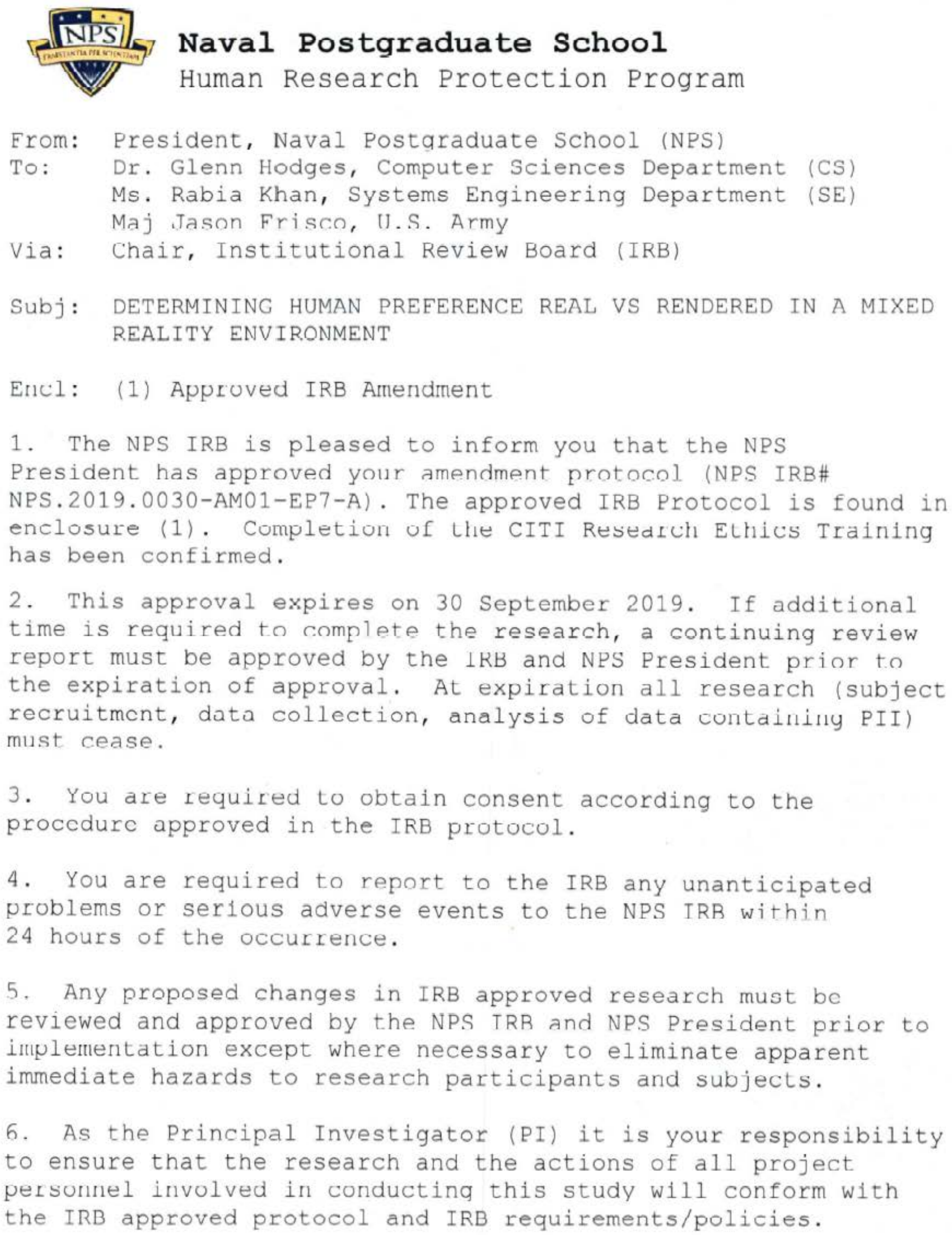
APPENDIX B. INSTITUTIONAL REVIEW BOARDS APPROVALS



Naval Postgraduate School
Human Research Protection Program

From: President, Naval Postgraduate School (NPS)
To: Dr. Glenn Hodges, Computer Sciences Department (CS)
Ms. Rabia Khan, Systems Engineering Department (SE)
Maj Jason Frisco, U.S. Army
Via: Chair, Institutional Review Board (IRB)

Subj: DETERMINING HUMAN PREFERENCE REAL VS RENDERED IN A MIXED REALITY ENVIRONMENT

Encl: (1) Approved IRB Amendment

1. The NPS IRB is pleased to inform you that the NPS President has approved your amendment protocol (NPS IRB# NPS.2019.0030-AM01-EP7-A). The approved IRB Protocol is found in enclosure (1). Completion of the CITI Research Ethics Training has been confirmed.

2. This approval expires on 30 September 2019. If additional time is required to complete the research, a continuing review report must be approved by the IRB and NPS President prior to the expiration of approval. At expiration all research (subject recruitment, data collection, analysis of data containing PII) must cease.

3. You are required to obtain consent according to the procedure approved in the IRB protocol.

4. You are required to report to the IRB any unanticipated problems or serious adverse events to the NPS IRB within 24 hours of the occurrence.

5. Any proposed changes in IRB approved research must be reviewed and approved by the NPS IRB and NPS President prior to implementation except where necessary to eliminate apparent immediate hazards to research participants and subjects.

6. As the Principal Investigator (PI) it is your responsibility to ensure that the research and the actions of all project personnel involved in conducting this study will conform with the IRB approved protocol and IRB requirements/policies.

Subj: DETERMINING HUMAN PREFERENCE REAL VS RENDERED IN A MIXED
REALITY ENVIRONMENT

7. At completion of the research, no later than expiration of approval, the PI will close the protocol by submitting a Final Report.

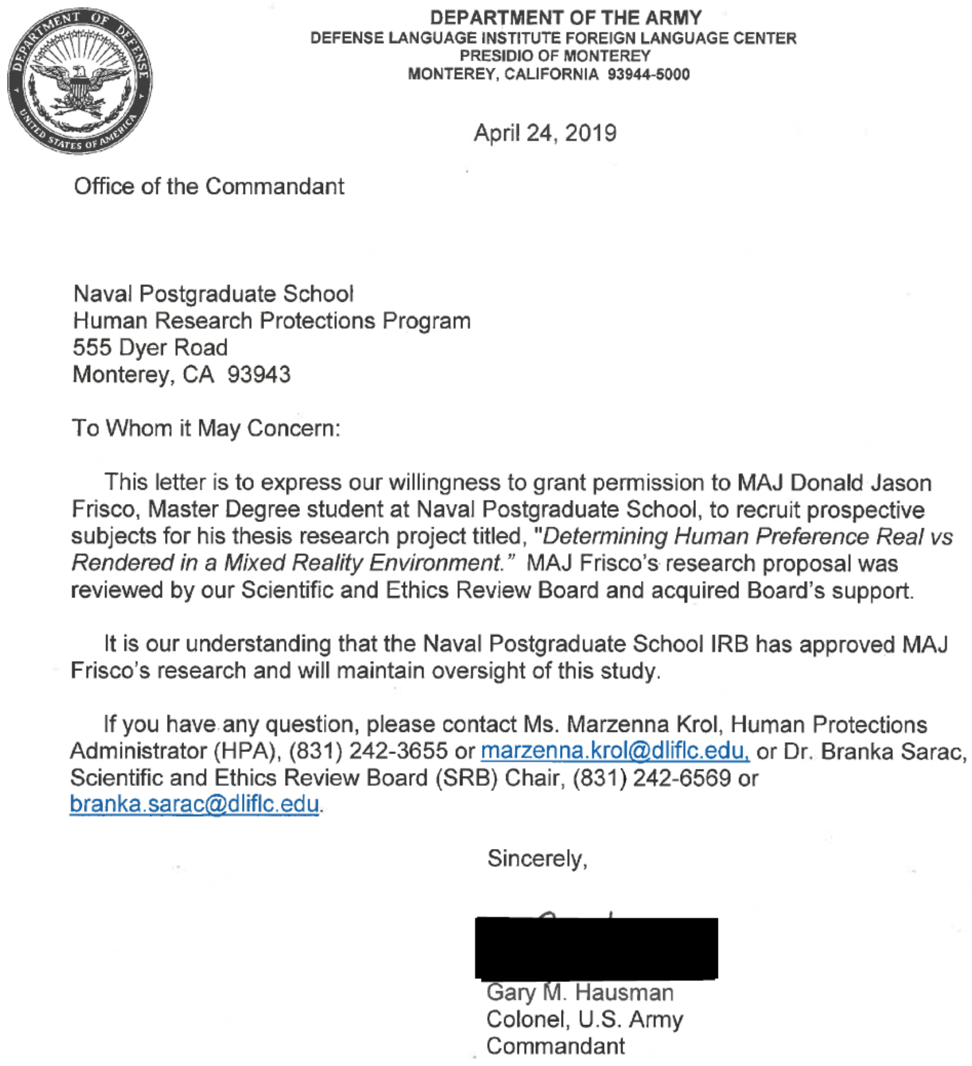
[redacted]

LAWRENCE G. SHATTUCK, PhD
Chair
Institutional Review Board

[redacted]

ANN E. RONDEAU, Ed.D.
Vice Admiral, U.S. Navy (Ret.)
President, Naval Postgraduate School

Date: 06 JUNE 2019



DEPARTMENT OF THE ARMY
DEFENSE LANGUAGE INSTITUTE FOREIGN LANGUAGE CENTER
PRESIDIO OF MONTEREY
MONTEREY, CALIFORNIA 93944-5000

April 24, 2019

Office of the Commandant

Naval Postgraduate School
Human Research Protections Program
555 Dyer Road
Monterey, CA 93943

To Whom it May Concern:

This letter is to express our willingness to grant permission to MAJ Donald Jason Frisco, Master Degree student at Naval Postgraduate School, to recruit prospective subjects for his thesis research project titled, "*Determining Human Preference Real vs Rendered in a Mixed Reality Environment.*" MAJ Frisco's research proposal was reviewed by our Scientific and Ethics Review Board and acquired Board's support.

It is our understanding that the Naval Postgraduate School IRB has approved MAJ Frisco's research and will maintain oversight of this study.

If you have any question, please contact Ms. Marzenna Krol, Human Protections Administrator (HPA), (831) 242-3655 or marzenna.krol@dliflc.edu, or Dr. Branka Sarac, Scientific and Ethics Review Board (SRB) Chair, (831) 242-6569 or branka.sarac@dliflc.edu.

Sincerely,

[redacted]
Gary M. Hausman
Colonel, U.S. Army
Commandant

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APPENDIX C. EXPERIMENT SCRIPT

Hello and Welcome,

You are about to take part in an experiment that will be used to help the Army and DoD with regard to the use of augmented reality technology.

This experiment uses the Magic Leap One AR-HMD (Show them the ML1 AR-HMD). After you complete the familiarization, you will be asked to enter the experiment room and conduct a search.

You are looking for this rubber duck (Hold up rubber duck). The rubber duck will be rendered, meaning it will be a computer image only seen through the ML1, and not real. Inside the room there will be real and rendered objects. The rubber duck is somewhere in the room, it can be anywhere in the room; in a real or rendered object, or in the wall, or on the floor. It is somewhere inside the room! Once you see the rubber duck you will use your fingers to make a pinching motion (demonstrate pinching motion) and the rubber duck will disappear and the experiment is over.

You will not need the remote for this experiment, it will only be used to make sure you can see the rendered remote over top of the real remote.

Do you have any questions at this time?

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APPENDIX D. POWER CALCULATION

Sample size = n (50-100)

Population size of active duty Army personnel = N (400,000)

critical value = $Z_{\alpha/2}^2$ (95%)

Margin of error = MOE (10%-13%)

sample proportion = p (30%-50%)

n = N*X / (X + N-1)

where X = $Z_{\alpha/2}^2 * p * (1-p) / MOE^2$

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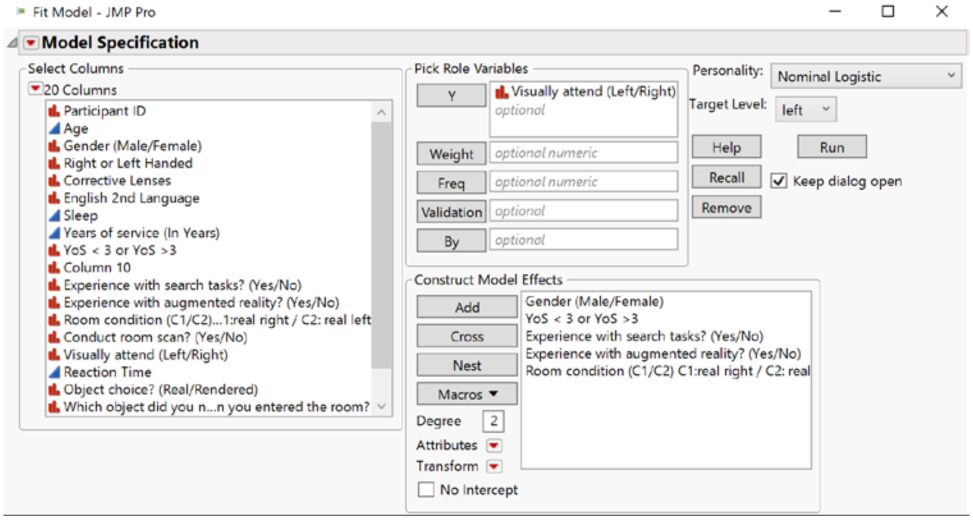
APPENDIX E. JMP STATISTICAL MODELING

Took our data set and ran a “Fit Model” on JMP that created a multiple logistic regression model (see Figure 22). Results from this model are seen in Figure 23



Y: Visually attend (Left/Right)

Personality: Nominal Logistic

Target Level: left

☑ Keep dialog open

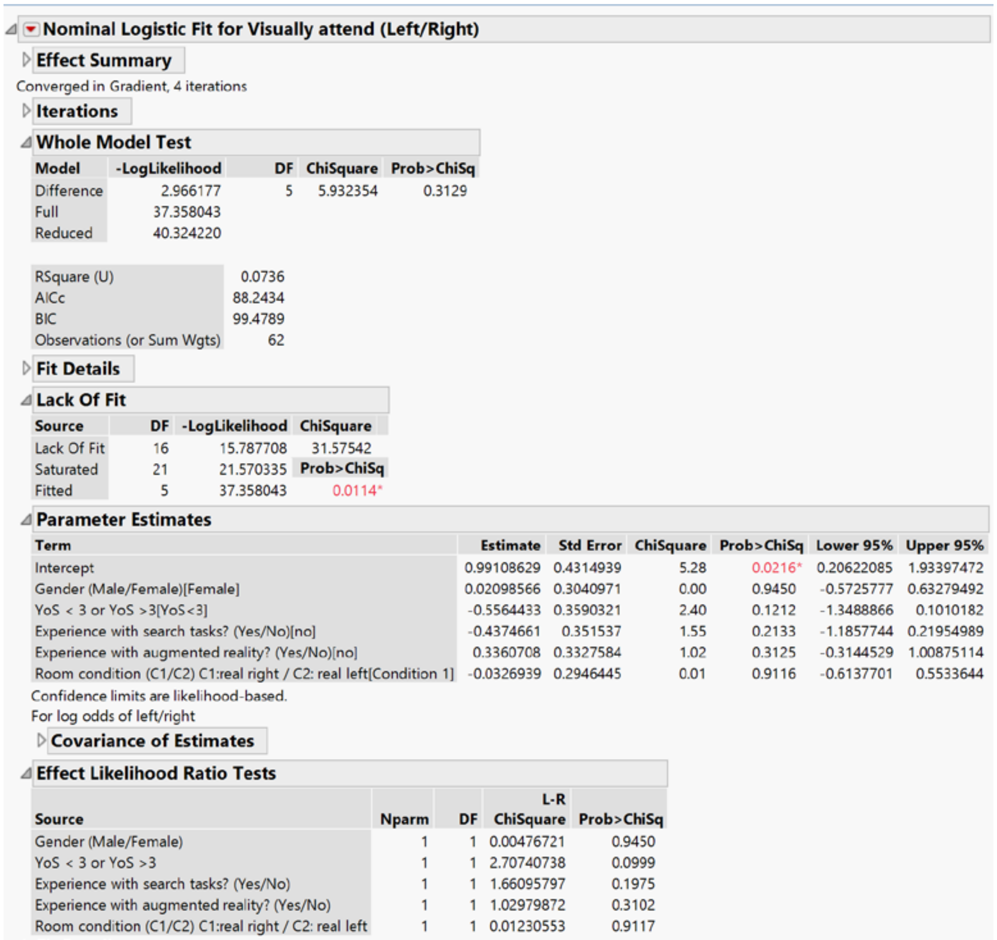
Degree: 2

☐ No Intercept

Construct Model Effects:

Gender (Male/Female)
YoS < 3 or YoS >3
Experience with search tasks? (Yes/No)
Experience with augmented reality? (Yes/No)
Room condition (C1/C2) C1:real right / C2: real

Figure 22. Visual attending JMP model



Nominal Logistic Fit for Visually attend (Left/Right)

Effect Summary

Converged in Gradient, 4 iterations

Iterations

Whole Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	2.966177	5	5.932354	0.3129
Full	37.358043			
Reduced	40.324220			

RSquare (U)	0.0736
AICc	88.2434
BIC	99.4789
Observations (or Sum Wgts)	62

Fit Details

Lack Of Fit

Source	DF	-LogLikelihood	ChiSquare
Lack Of Fit	16	15.787708	31.57542
Saturated	21	21.570335	**Prob>ChiSq**
Fitted	5	37.358043	0.0114*

Parameter Estimates

Term	Estimate	Std Error	ChiSquare	Prob>ChiSq	Lower 95%	Upper 95%
Intercept	0.99108629	0.4314939	5.28	0.0216*	0.20622085	1.93397472
Gender (Male/Female)[Female]	0.02098566	0.3040971	0.00	0.9450	-0.5725777	0.63279492
YoS < 3 or YoS >3[YoS<3]	-0.5564433	0.3590321	2.40	0.1212	-1.3488866	0.1010182
Experience with search tasks? (Yes/No)[no]	-0.4374661	0.351537	1.55	0.2133	-1.1857744	0.21954989
Experience with augmented reality? (Yes/No)[no]	0.3360708	0.3327584	1.02	0.3125	-0.3144529	1.00875114
Room condition (C1/C2) C1:real right / C2: real left[Condition 1]	-0.0326939	0.2946445	0.01	0.9116	-0.6137701	0.5533644

Confidence limits are likelihood-based.

For log odds of left/right

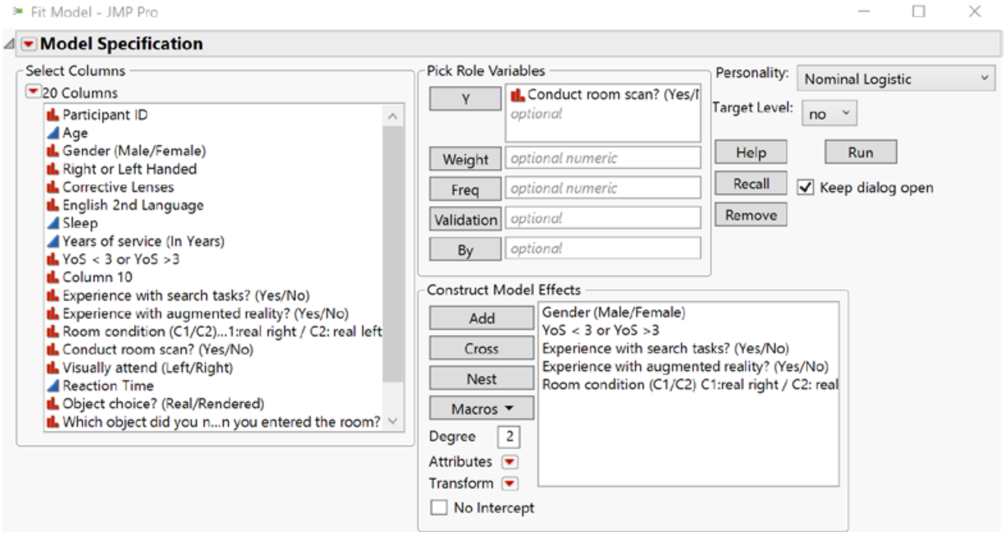
Covariance of Estimates

Effect Likelihood Ratio Tests

Source	Nparm	DF	L-R ChiSquare	Prob>ChiSq
Gender (Male/Female)	1	1	0.00476721	0.9450
YoS < 3 or YoS >3	1	1	2.70740738	0.0999
Experience with search tasks? (Yes/No)	1	1	1.66095797	0.1975
Experience with augmented reality? (Yes/No)	1	1	1.02979872	0.3102
Room condition (C1/C2) C1:real right / C2: real left	1	1	0.01230553	0.9117

Figure 23. Model results from visual attending

Next we conduct a multiple logistic regression model for room scan (see Figure 24). Results from this model are shown in Figure 25.



20 Columns

- Participant ID
- Age
- Gender (Male/Female)
- Right or Left Handed
- Corrective Lenses
- English 2nd Language
- Sleep
- Years of service (In Years)
- YoS < 3 or YoS >3
- Column 10
- Experience with search tasks? (Yes/No)
- Experience with augmented reality? (Yes/No)
- Room condition (C1/C2)...1:real right / C2: real left
- Conduct room scan? (Yes/No)
- Visually attend (Left/Right)
- Reaction Time
- Object choice? (Real/Rendered)
- Which object did you n...n you entered the room?

Y: Conduct room scan? (Yes/I

Personality: Nominal Logistic

Target Level: no

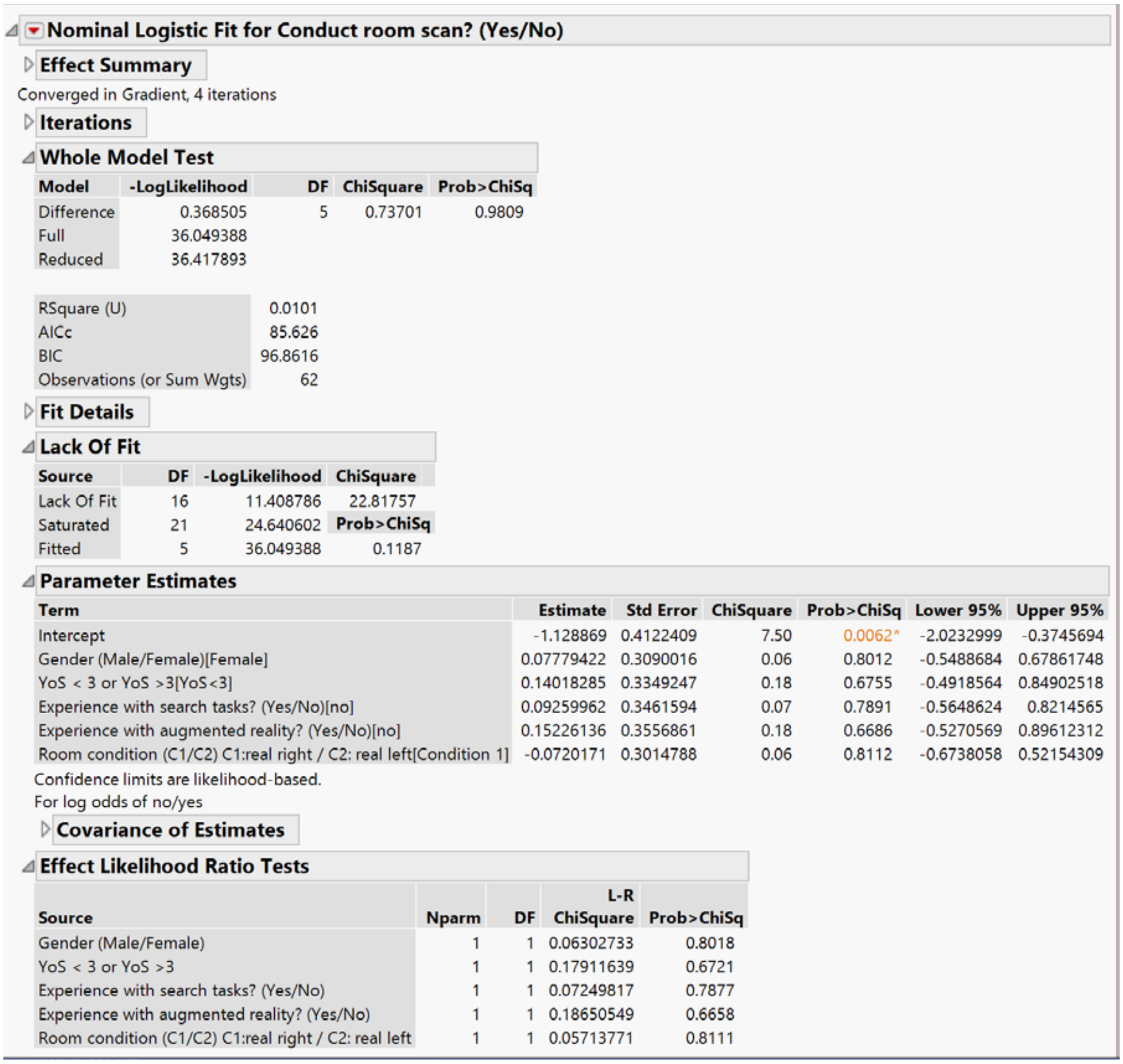
☑ Keep dialog open

Degree 2

☐ No Intercept

Gender (Male/Female)
YoS < 3 or YoS >3
Experience with search tasks? (Yes/No)
Experience with augmented reality? (Yes/No)
Room condition (C1/C2) C1:real right / C2: real

Figure 24. Room scan JMP model



Nominal Logistic Fit for Conduct room scan? (Yes/No)

Effect Summary

Converged in Gradient, 4 iterations

Iterations

Whole Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	0.368505	5	0.73701	0.9809
Full	36.049388			
Reduced	36.417893			

RSquare (U)	0.0101
AICc	85.626
BIC	96.8616
Observations (or Sum Wgts)	62

Fit Details

Lack Of Fit

Source	DF	-LogLikelihood	ChiSquare
Lack Of Fit	16	11.408786	22.81757
Saturated	21	24.640602	**Prob>ChiSq**
Fitted	5	36.049388	0.1187

Parameter Estimates

Term	Estimate	Std Error	ChiSquare	Prob>ChiSq	Lower 95%	Upper 95%
Intercept	-1.128869	0.4122409	7.50	0.0062*	-2.0232999	-0.3745694
Gender (Male/Female)[Female]	0.07779422	0.3090016	0.06	0.8012	-0.5488684	0.67861748
YoS < 3 or YoS >3[YoS<3]	0.14018285	0.3349247	0.18	0.6755	-0.4918564	0.84902518
Experience with search tasks? (Yes/No)[no]	0.09259962	0.3461594	0.07	0.7891	-0.5648624	0.8214565
Experience with augmented reality? (Yes/No)[no]	0.15226136	0.3556861	0.18	0.6686	-0.5270569	0.89612312
Room condition (C1/C2) C1:real right / C2: real left[Condition 1]	-0.0720171	0.3014788	0.06	0.8112	-0.6738058	0.52154309

Confidence limits are likelihood-based.
For log odds of no/yes

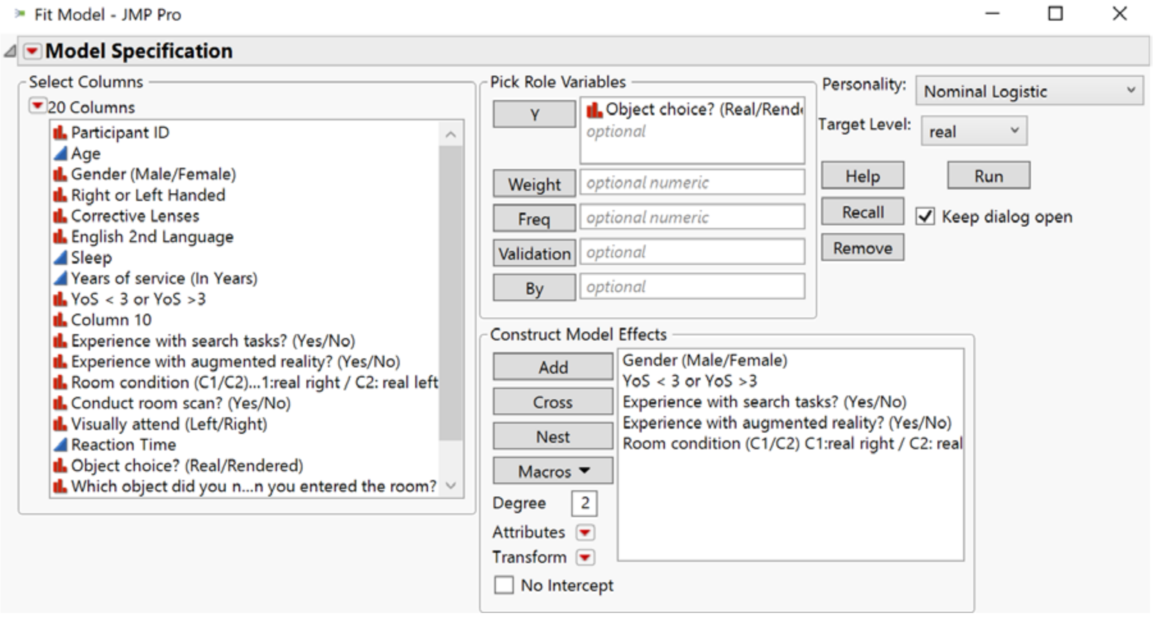
Covariance of Estimates

Effect Likelihood Ratio Tests

Source	Nparm	DF	L-R ChiSquare	Prob>ChiSq
Gender (Male/Female)	1	1	0.06302733	0.8018
YoS < 3 or YoS >3	1	1	0.17911639	0.6721
Experience with search tasks? (Yes/No)	1	1	0.07249817	0.7877
Experience with augmented reality? (Yes/No)	1	1	0.18650549	0.6658
Room condition (C1/C2) C1:real right / C2: real left	1	1	0.05713771	0.8111

Figure 25. Model results for conducting room scan

Next a multiple logistic regression model was conducted for object choice (see Figure 26).



20 Columns
- Participant ID
- Age
- Gender (Male/Female)
- Right or Left Handed
- Corrective Lenses
- English 2nd Language
- Sleep
- Years of service (In Years)
- YoS < 3 or YoS >3
- Column 10
- Experience with search tasks? (Yes/No)
- Experience with augmented reality? (Yes/No)
- Room condition (C1/C2)...1:real right / C2: real left
- Conduct room scan? (Yes/No)
- Visually attend (Left/Right)
- Reaction Time
- Object choice? (Real/Rendered)
- Which object did you n...n you entered the room?

Y: Object choice? (Real/Rend

Personality: Nominal Logistic

Target Level: real

☑ Keep dialog open

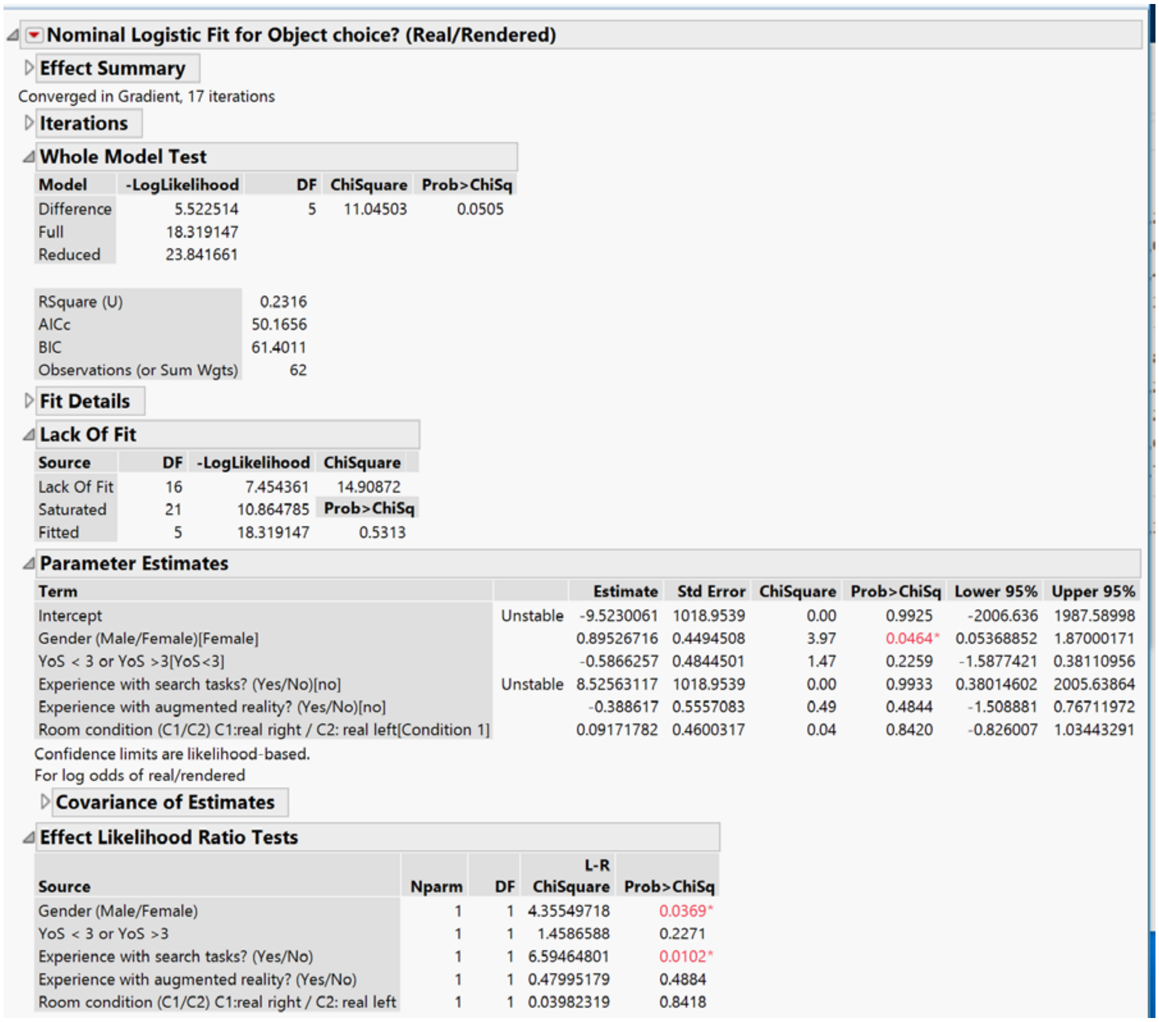
Model effects:
- Gender (Male/Female)
- YoS < 3 or YoS >3
- Experience with search tasks? (Yes/No)
- Experience with augmented reality? (Yes/No)
- Room condition (C1/C2) C1:real right / C2: real

Degree 2

☐ No Intercept

Figure 26. JMP model for object choice

Results from the first object choice model are shown in Figure 27. Since this model showed statistical significance we conducted backwards reduction by running the model with less potential predictors see Figure 28 and Figure 29 for results.



Nominal Logistic Fit for Object choice? (Real/Rendered)

Effect Summary

Converged in Gradient, 17 iterations

Iterations

Whole Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	5.522514	5	11.04503	0.0505
Full	18.319147			
Reduced	23.841661			

RSquare (U)	0.2316
AICc	50.1656
BIC	61.4011
Observations (or Sum Wgts)	62

Fit Details

Lack Of Fit

Source	DF	-LogLikelihood	ChiSquare
Lack Of Fit	16	7.454361	14.90872
Saturated	21	10.864785	**Prob>ChiSq**
Fitted	5	18.319147	0.5313

Parameter Estimates

Term		Estimate	Std Error	ChiSquare	Prob>ChiSq	Lower 95%	Upper 95%
Intercept	Unstable	-9.5230061	1018.9539	0.00	0.9925	-2006.636	1987.58998
Gender (Male/Female)[Female]		0.89526716	0.4494508	3.97	0.0464*	0.05368852	1.87000171
YoS < 3 or YoS >3[YoS<3]		-0.5866257	0.4844501	1.47	0.2259	-1.5877421	0.38110956
Experience with search tasks? (Yes/No)[no]	Unstable	8.52563117	1018.9539	0.00	0.9933	0.38014602	2005.63864
Experience with augmented reality? (Yes/No)[no]		-0.388617	0.5557083	0.49	0.4844	-1.508881	0.76711972
Room condition (C1/C2) C1:real right / C2: real left[Condition 1]		0.09171782	0.4600317	0.04	0.8420	-0.826007	1.03443291

Confidence limits are likelihood-based.

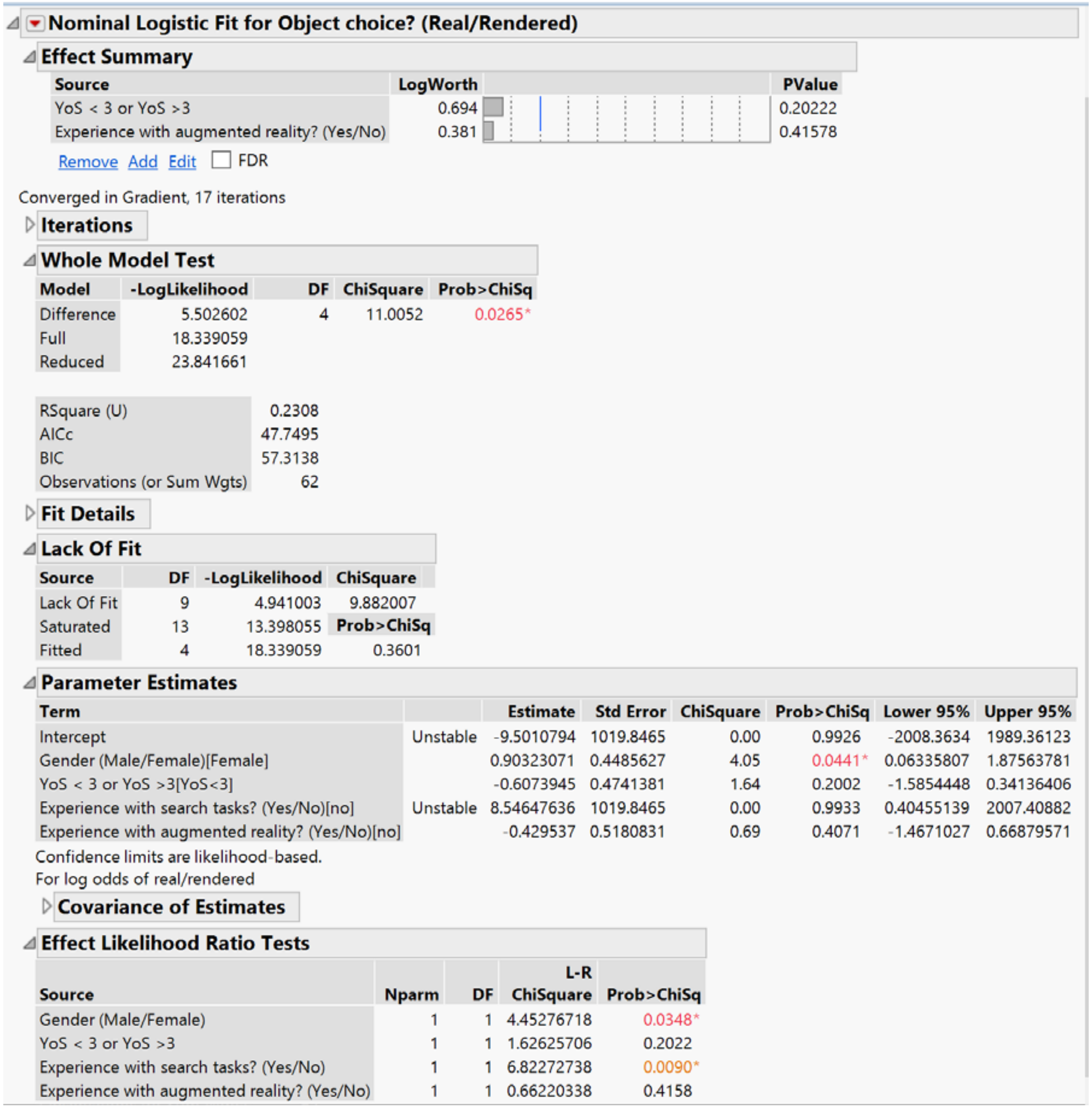
For log odds of real/rendered

Covariance of Estimates

Effect Likelihood Ratio Tests

Source	Nparm	DF	L-R ChiSquare	Prob>ChiSq
Gender (Male/Female)	1	1	4.35549718	0.0369*
YoS < 3 or YoS >3	1	1	1.4586588	0.2271
Experience with search tasks? (Yes/No)	1	1	6.59464801	0.0102*
Experience with augmented reality? (Yes/No)	1	1	0.47995179	0.4884
Room condition (C1/C2) C1:real right / C2: real left	1	1	0.03982319	0.8418

Figure 27. JMP model 1 for object choice



Nominal Logistic Fit for Object choice? (Real/Rendered)

Effect Summary

Source	LogWorth	PValue
YoS < 3 or YoS >3	0.694	0.20222
Experience with augmented reality? (Yes/No)	0.381	0.41578

Remove Add Edit ☐ FDR

Converged in Gradient, 17 iterations

Iterations

Whole Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	5.502602	4	11.0052	0.0265*
Full	18.339059			
Reduced	23.841661			

RSquare (U)	0.2308
AICc	47.7495
BIC	57.3138
Observations (or Sum Wgts)	62

Fit Details

Lack Of Fit

Source	DF	-LogLikelihood	ChiSquare
Lack Of Fit	9	4.941003	9.882007
Saturated	13	13.398055	**Prob>ChiSq**
Fitted	4	18.339059	0.3601

Parameter Estimates

Term		Estimate	Std Error	ChiSquare	Prob>ChiSq	Lower 95%	Upper 95%
Intercept	Unstable	-9.5010794	1019.8465	0.00	0.9926	-2008.3634	1989.36123
Gender (Male/Female)[Female]		0.90323071	0.4485627	4.05	0.0441*	0.06335807	1.87563781
YoS < 3 or YoS >3[YoS<3]		-0.6073945	0.4741381	1.64	0.2002	-1.5854448	0.34136406
Experience with search tasks? (Yes/No)[no]	Unstable	8.54647636	1019.8465	0.00	0.9933	0.40455139	2007.40882
Experience with augmented reality? (Yes/No)[no]		-0.429537	0.5180831	0.69	0.4071	-1.4671027	0.66879571

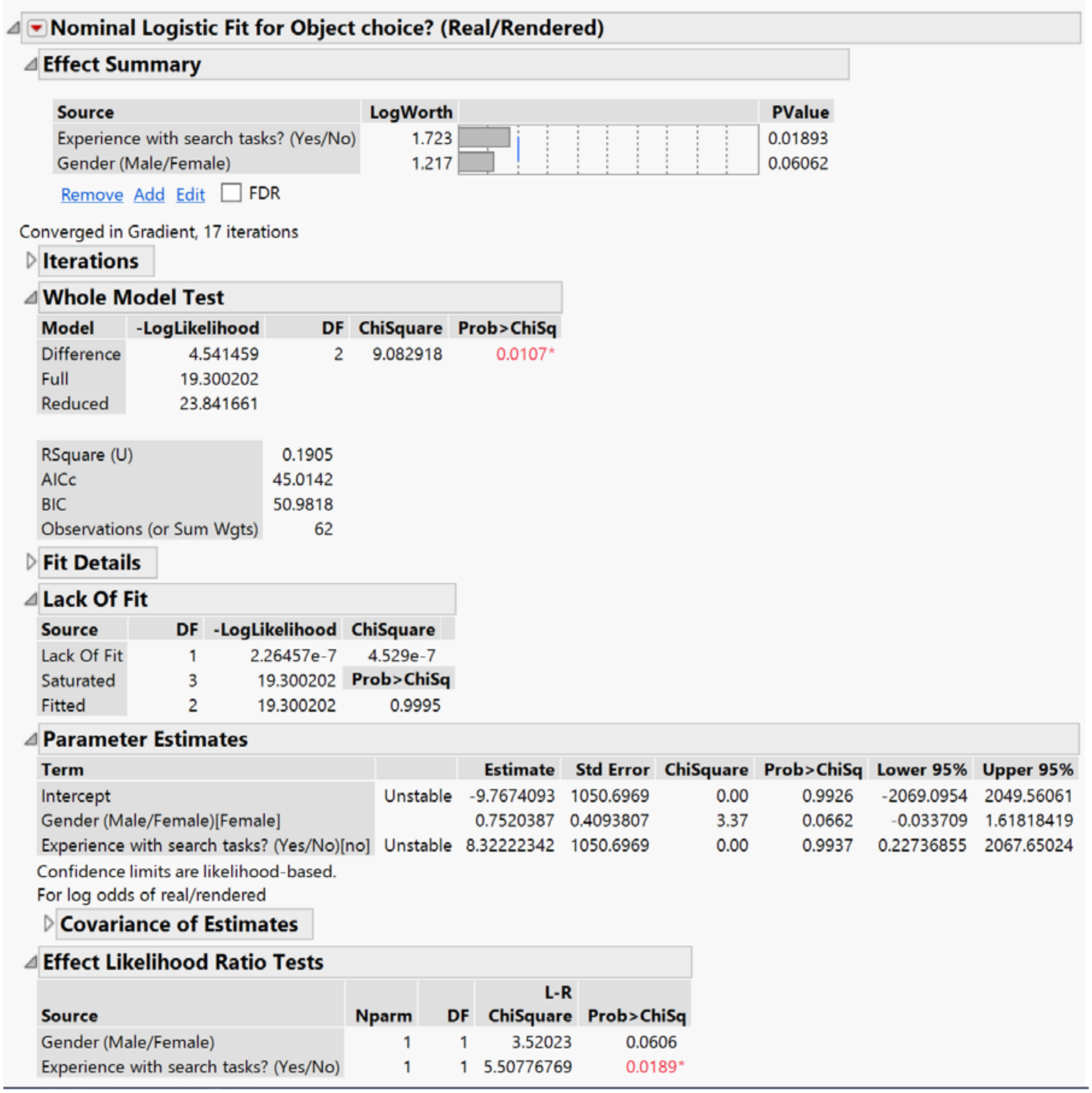
Confidence limits are likelihood-based.
For log odds of real/rendered

Covariance of Estimates

Effect Likelihood Ratio Tests

Source	Nparm	DF	L-R ChiSquare	Prob>ChiSq
Gender (Male/Female)	1	1	4.45276718	0.0348*
YoS < 3 or YoS >3	1	1	1.62625706	0.2022
Experience with search tasks? (Yes/No)	1	1	6.82272738	0.0090*
Experience with augmented reality? (Yes/No)	1	1	0.66220338	0.4158

Figure 28. JMP model 2 for object choice



Nominal Logistic Fit for Object choice? (Real/Rendered)

Effect Summary

Source	LogWorth	PValue
Experience with search tasks? (Yes/No)	1.723	0.01893
Gender (Male/Female)	1.217	0.06062

Converged in Gradient, 17 iterations

Whole Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	4.541459	2	9.082918	0.0107*
Full	19.300202			
Reduced	23.841661			

RSquare (U)	0.1905
AICc	45.0142
BIC	50.9818
Observations (or Sum Wgts)	62

Lack Of Fit

Source	DF	-LogLikelihood	ChiSquare
Lack Of Fit	1	2.26457e-7	4.529e-7
Saturated	3	19.300202	Prob>ChiSq
Fitted	2	19.300202	0.9995

Parameter Estimates

Term		Estimate	Std Error	ChiSquare	Prob>ChiSq	Lower 95%	Upper 95%
Intercept	Unstable	-9.7674093	1050.6969	0.00	0.9926	-2069.0954	2049.56061
Gender (Male/Female)[Female]		0.7520387	0.4093807	3.37	0.0662	-0.033709	1.61818419
Experience with search tasks? (Yes/No)[no]	Unstable	8.32222342	1050.6969	0.00	0.9937	0.22736855	2067.65024

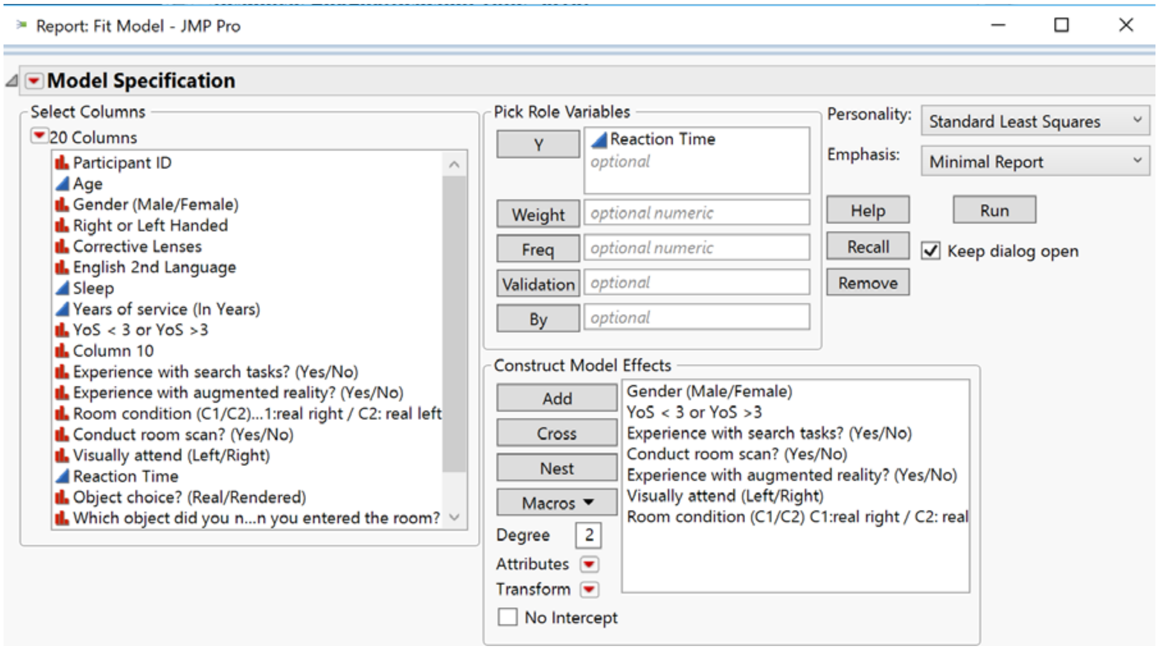
Confidence limits are likelihood-based.
For log odds of real/rendered

Effect Likelihood Ratio Tests

Source	Nparm	DF	L-R ChiSquare	Prob>ChiSq
Gender (Male/Female)	1	1	3.52023	0.0606
Experience with search tasks? (Yes/No)	1	1	5.50776769	0.0189*

Figure 29. JMP model 3 for object choice

A multiple regression was conducted for time to complete the task (see Figure 30). From the result box-cox Y transform was selected and replace with transforms was selected. Results from this model are shown in Figure 31. Since the first model was significant we conducted backward reduction to create two additional models. Results from model 2 and model 3 are shown in Figure 32 and Figure 33.



Model Specification

Select Columns

20 Columns

- Participant ID
- Age
- Gender (Male/Female)
- Right or Left Handed
- Corrective Lenses
- English 2nd Language
- Sleep
- Years of service (In Years)
- YoS < 3 or YoS >3
- Column 10
- Experience with search tasks? (Yes/No)
- Experience with augmented reality? (Yes/No)
- Room condition (C1/C2)...1:real right / C2: real left
- Conduct room scan? (Yes/No)
- Visually attend (Left/Right)
- Reaction Time
- Object choice? (Real/Rendered)
- Which object did you n...n you entered the room?

Y: Reaction Time

Personality: Standard Least Squares

Emphasis: Minimal Report

☑ Keep dialog open

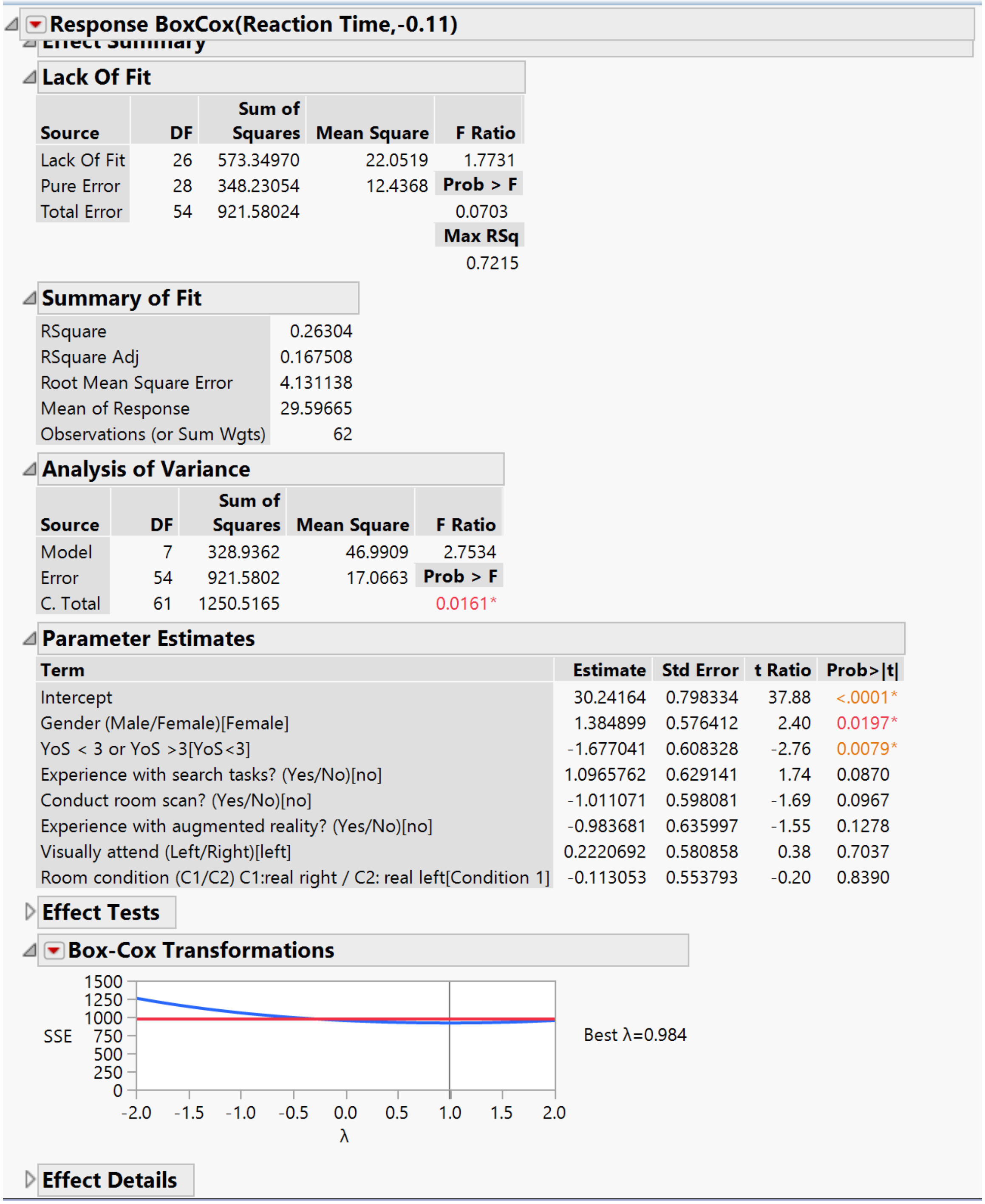
Construct Model Effects

- Gender (Male/Female)
- YoS < 3 or YoS >3
- Experience with search tasks? (Yes/No)
- Conduct room scan? (Yes/No)
- Experience with augmented reality? (Yes/No)
- Visually attend (Left/Right)
- Room condition (C1/C2) C1:real right / C2: real

Degree 2

☐ No Intercept

Figure 30. JMP model for time to complete task



Response BoxCox(Reaction Time,-0.11)

Effect Summary

Lack Of Fit

Source	DF	Sum of Squares	Mean Square	F Ratio
Lack Of Fit	26	573.34970	22.0519	1.7731
Pure Error	28	348.23054	12.4368	**Prob > F**
Total Error	54	921.58024		0.0703
				Max RSq
				0.7215

Summary of Fit

RSquare	0.26304
RSquare Adj	0.167508
Root Mean Square Error	4.131138
Mean of Response	29.59665
Observations (or Sum Wgts)	62

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	7	328.9362	46.9909	2.7534
Error	54	921.5802	17.0663	**Prob > F**
C. Total	61	1250.5165		0.0161*

Parameter Estimates

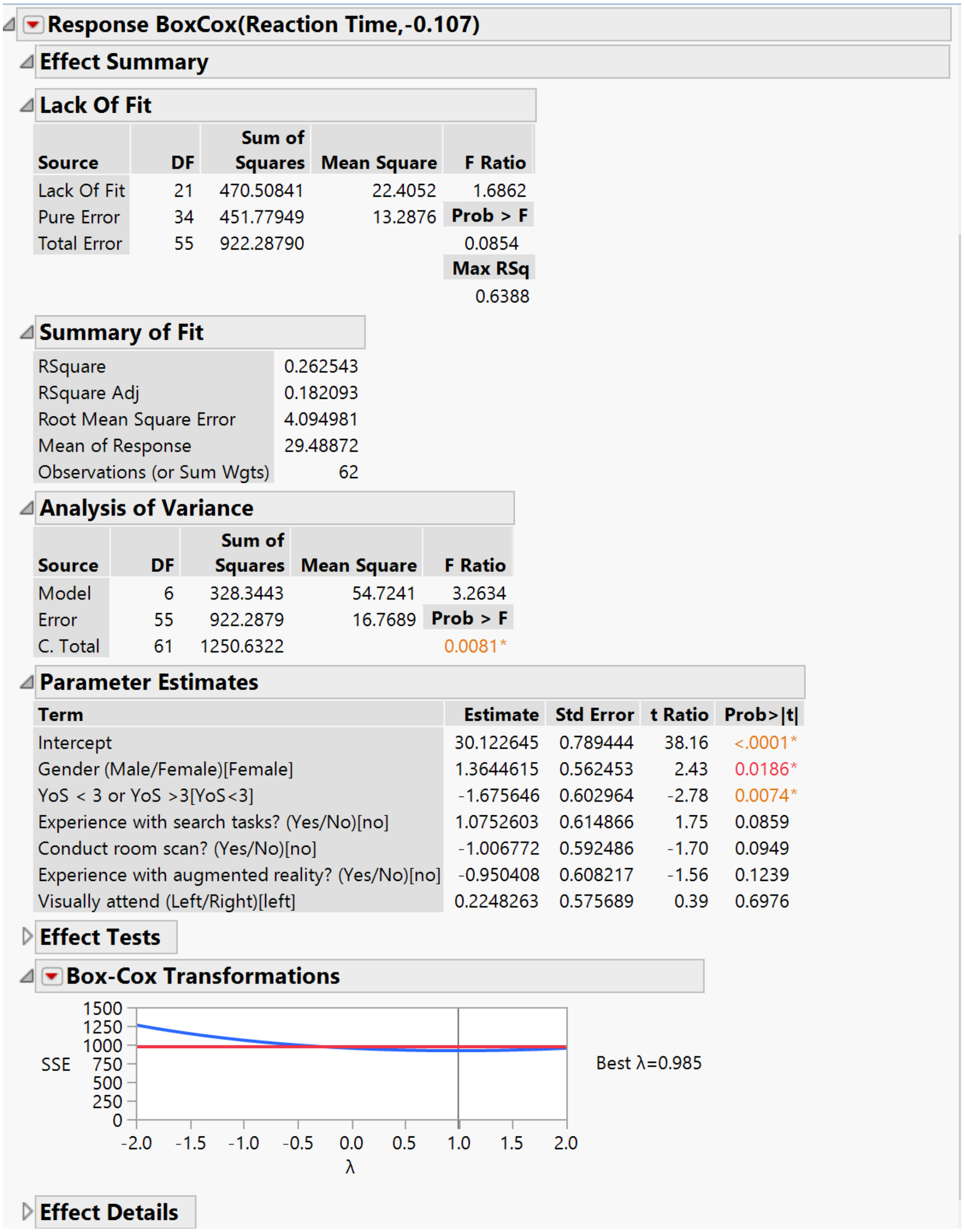
Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	30.24164	0.798334	37.88	<.0001*
Gender (Male/Female)[Female]	1.384899	0.576412	2.40	0.0197*
YoS < 3 or YoS >3[YoS<3]	-1.677041	0.608328	-2.76	0.0079*
Experience with search tasks? (Yes/No)[no]	1.0965762	0.629141	1.74	0.0870
Conduct room scan? (Yes/No)[no]	-1.011071	0.598081	-1.69	0.0967
Experience with augmented reality? (Yes/No)[no]	-0.983681	0.635997	-1.55	0.1278
Visually attend (Left/Right)[left]	0.2220692	0.580858	0.38	0.7037
Room condition (C1/C2) C1:real right / C2: real left[Condition 1]	-0.113053	0.553793	-0.20	0.8390

Effect Tests

Box-Cox Transformations

Effect Details

Figure 31. Results JMP model 1 time to complete task



Response BoxCox(Reaction Time,-0.107)

Effect Summary

Lack Of Fit

Source	DF	Sum of Squares	Mean Square	F Ratio
Lack Of Fit	21	470.50841	22.4052	1.6862
Pure Error	34	451.77949	13.2876	**Prob > F**
Total Error	55	922.28790		0.0854
				Max RSq
				0.6388

Summary of Fit

RSquare	0.262543
RSquare Adj	0.182093
Root Mean Square Error	4.094981
Mean of Response	29.48872
Observations (or Sum Wgts)	62

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	6	328.3443	54.7241	3.2634
Error	55	922.2879	16.7689	**Prob > F**
C. Total	61	1250.6322		0.0081*

Parameter Estimates

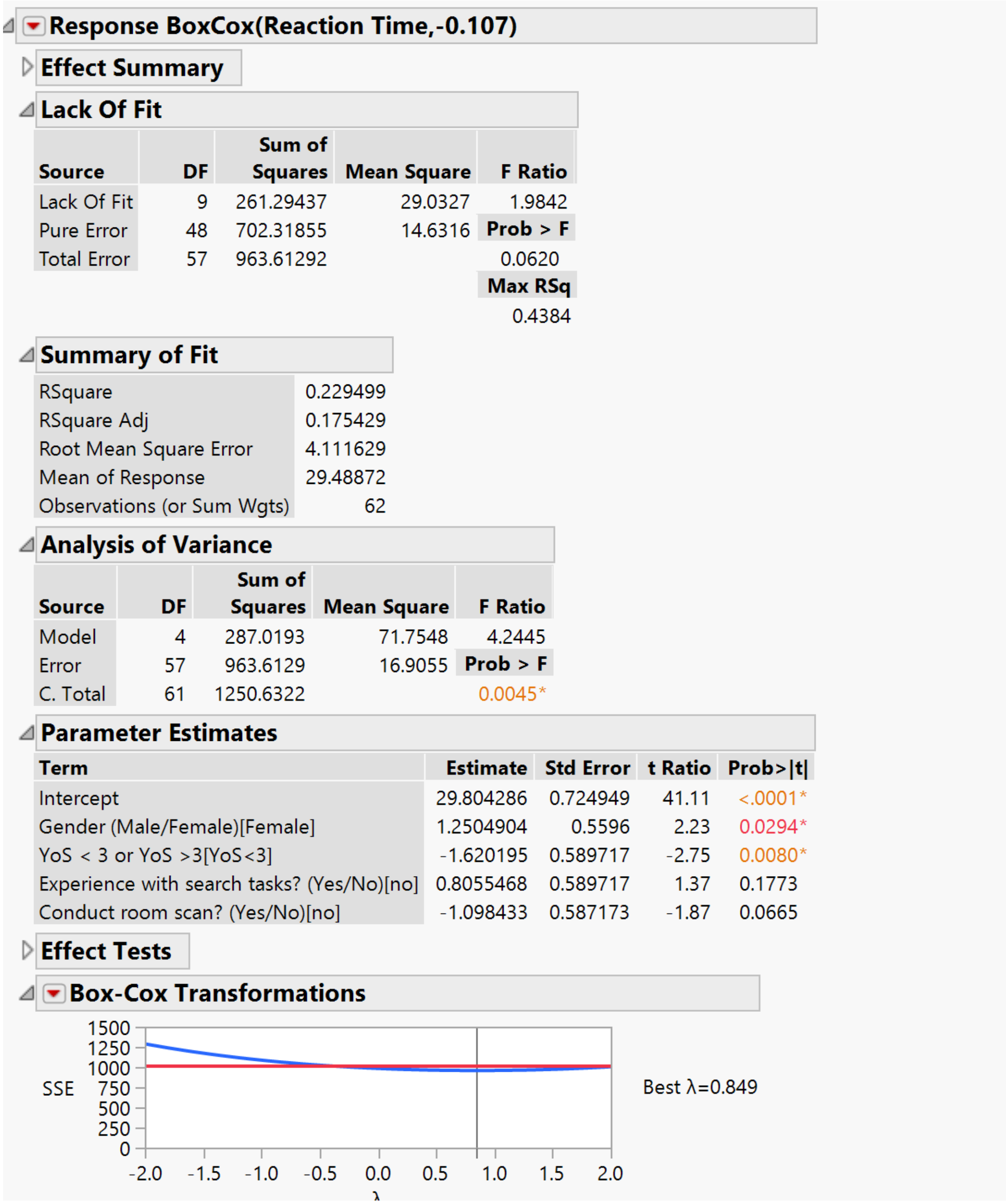
Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	30.122645	0.789444	38.16	<.0001*
Gender (Male/Female)[Female]	1.3644615	0.562453	2.43	0.0186*
YoS < 3 or YoS >3[YoS<3]	-1.675646	0.602964	-2.78	0.0074*
Experience with search tasks? (Yes/No)[no]	1.0752603	0.614866	1.75	0.0859
Conduct room scan? (Yes/No)[no]	-1.006772	0.592486	-1.70	0.0949
Experience with augmented reality? (Yes/No)[no]	-0.950408	0.608217	-1.56	0.1239
Visually attend (Left/Right)[left]	0.2248263	0.575689	0.39	0.6976

Effect Tests

Box-Cox Transformations

Effect Details

Figure 32. Results JMP model 2 time to complete task



Response BoxCox(Reaction Time,-0.107)

Effect Summary

Lack Of Fit

Source	DF	Sum of Squares	Mean Square	F Ratio
Lack Of Fit	9	261.29437	29.0327	1.9842
Pure Error	48	702.31855	14.6316	**Prob > F**
Total Error	57	963.61292		0.0620
				Max RSq
				0.4384

Summary of Fit

RSquare	0.229499
RSquare Adj	0.175429
Root Mean Square Error	4.111629
Mean of Response	29.48872
Observations (or Sum Wgts)	62

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	4	287.0193	71.7548	4.2445
Error	57	963.6129	16.9055	**Prob > F**
C. Total	61	1250.6322		0.0045*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	29.804286	0.724949	41.11	<.0001*
Gender (Male/Female)[Female]	1.2504904	0.5596	2.23	0.0294*
YoS < 3 or YoS >3[YoS<3]	-1.620195	0.589717	-2.75	0.0080*
Experience with search tasks? (Yes/No)[no]	0.8055468	0.589717	1.37	0.1773
Conduct room scan? (Yes/No)[no]	-1.098433	0.587173	-1.87	0.0665

Effect Tests

Box-Cox Transformations

Figure 33. Results JMP model 3 time to complete task

For data list for this study please contact Glenn Hodges at gahodges1@nps.edu.

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