ENHANCING COLLABORATOR COMMUNICATION THROUGH SHARED-GAZE VISUALIZATIONS IN AUGMENTED REALITY

By

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Abstract of Dissertation Presented to the Graduate School
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The fourth industrial revolution has increased the demand for smart manufacturing tools that support human workers in real time—particularly through augmented reality (AR), which can enhance situational awareness and communication during complex tasks. While AR offers benefits such as improved process skills and multi-modal support in noisy environments, current head-mounted displays often hinder social cues like eye contact. Since eye gaze is essential for effective collaboration, there is a growing need for gaze-visualization techniques that preserve AR's advantages without overwhelming or distracting users, as some prior implementations have done. Recognizing the potential of AR in industrial settings and the importance of shared gaze in collaborative contexts, this dissertation investigates the question: ***How can we aid collaborators in industrial tasks through shared-gaze information in augmented reality?*** The studies presented in this dissertation highlight the importance of preserving user control and privacy in shared-gaze visualizations. They offer insights into users' perceptions of self-gaze in collaborative settings and demonstrate how external stimuli influence users' perception and interaction with shared-gaze visualizations. This dissertation identifies key design principles for shared-gaze visualizations that balance collaboration with user autonomy. It provides an understanding of how self-gaze affects user perception of shared-gaze, presents evidence that sound significantly shapes these perceptions, and offers design recommendations for enhancing collaborative experiences in augmented reality. It also outlines promising directions for future research.

CHAPTER 1
INTRODUCTION

Industry 4.0 represents the fourth industrial revolution and involves integrating smart manufacturing devices into production processes. This era has introduced the digitization of manufacturing and the development of ”smart factories” [64, 83, 104]. While known as ”Industry 4.0” in Germany [104] and the ”Advanced Manufacturing Partnership” in the United States [42], both initiatives aim to decrease material preparation time, enhance manufacturing energy efficiency, and create technologies that significantly reduce the timeframes for designing, building, and testing manufactured products [3, 72, 104].

Compared to prior industry practices of automated Computer Integrated Manufacturing (CIM), Industry 4.0 places emphasis on the human role in production [130, 174]. Through the integration of context-aware technologies, smart manufacturing environments are capable of providing real-time feedback and error prevention [129, 177]. Additionally, systems are capable of supporting production workers through guiding technologies such as providing augmented reality instructions to users [177], further aiding in collaborative design [183], and improving processing skills [54].

Augmented reality (AR) provides a unique opportunity for enhancing human-computer interactions and collaborator communication [150]. AR has the capability of expanding on a worker’s abilities through guidance and optimizing decisions [36], improving their occupational safety [110, 172], and improving their situational awareness [45, 190]. Augmented information can be provided through visualizations, overlaid on the environment or in the headsets’ visor [12, 190], and audio instructions [29, 150]. Voice commands and gestural controls, while commonly implemented in augmented reality headsets, face significant limitations in environments with high noise levels, including assembly lines [56, 73] and construction sites [94]. Additionally, users may not always have all modalities of interaction available, since their hands may be occupied [66], they may be focused on a task [90, 197, 198], or can not readily listen due to a noisy environment [150, 154].

Despite the benefits of augmented reality, one drawback of AR is that physical headsets can block out non-verbal communication cues such as eye-contact [147]. Nonverbal communication is important in industrial environments since it is noisy and speech is limited [20, 56]. Additionally, the occlusion of facial expressions by head mounted displays presents a challenge to collaboration [147, 160]. Eye-contact is a fundamental human trait that is essential to social and group interactions [99, 189]. Observed changes in eye movements between members provides an influential non-verbal cue that affects how decisions are made [99, 167] and allows collaborators to gauge each others' intentions [71, 99]. Thus, there is a need for developing gaze-visualization techniques for collaborators working with head-mounted displays [16, 91, 198].

With the integration of eye-tracking into modern head mounted displays [109, 143], prior work has looked at supporting shared-gaze interactions through fixation points, heat maps, and areas of focus [139, 170]. Gaze visualizations can enhance normal face-to-face interactions by clarifying vague phrases such as ”it is over there” and providing a clearer representation of internal thought processes [159]. Despite the benefits to enhancing collaborator communication, current implementations of gaze visualizations have been found to be overwhelming [170] and distracting [51]. Additionally, prior methods suffer from lack of control [87, 90, 178], balancing performance and user preferences [33], and privacy issues [198].

Understanding the existing limitations when extending collaborative augmented reality to industrial applications, this dissertation aims to understand how can we aid collaborators through shared-gaze information by further investigating:

1. *How can we present shared-gaze visualizations while preserving user's sense of control and privacy over the visualizations during an assembly task?*
2. *How does self-gaze affect user perception of shared-gazed visualizations in augmented reality?*
3. *How does audio noise alter users' perceptions of shared-gaze visualization?*

Outline This dissertation comprises eight chapters. It begins with an Introduction (1), followed by a Background chapter (2) that presents an extensive analysis of related work. The third chapter

(3) presents a description of the system implemented to support the following evluation. The fourth chapter (4) evaluates Shared-Gaze Visualizations for virtual assembly tasks, while the fifth (5) explores Self-Gaze for Collocated Tasks in Augmented Reality. Chapter six (6) examines the effects of sound on the perception of shared-gaze visualizations in an industrial sorting task with visual cues. The dissertation concludes with two chapters: Discussion and future work (7), and finally, Conclusions of my work and its contributions (8). A flow diagram of research questions, the research conducted and their findings is presented in Figure 1-1

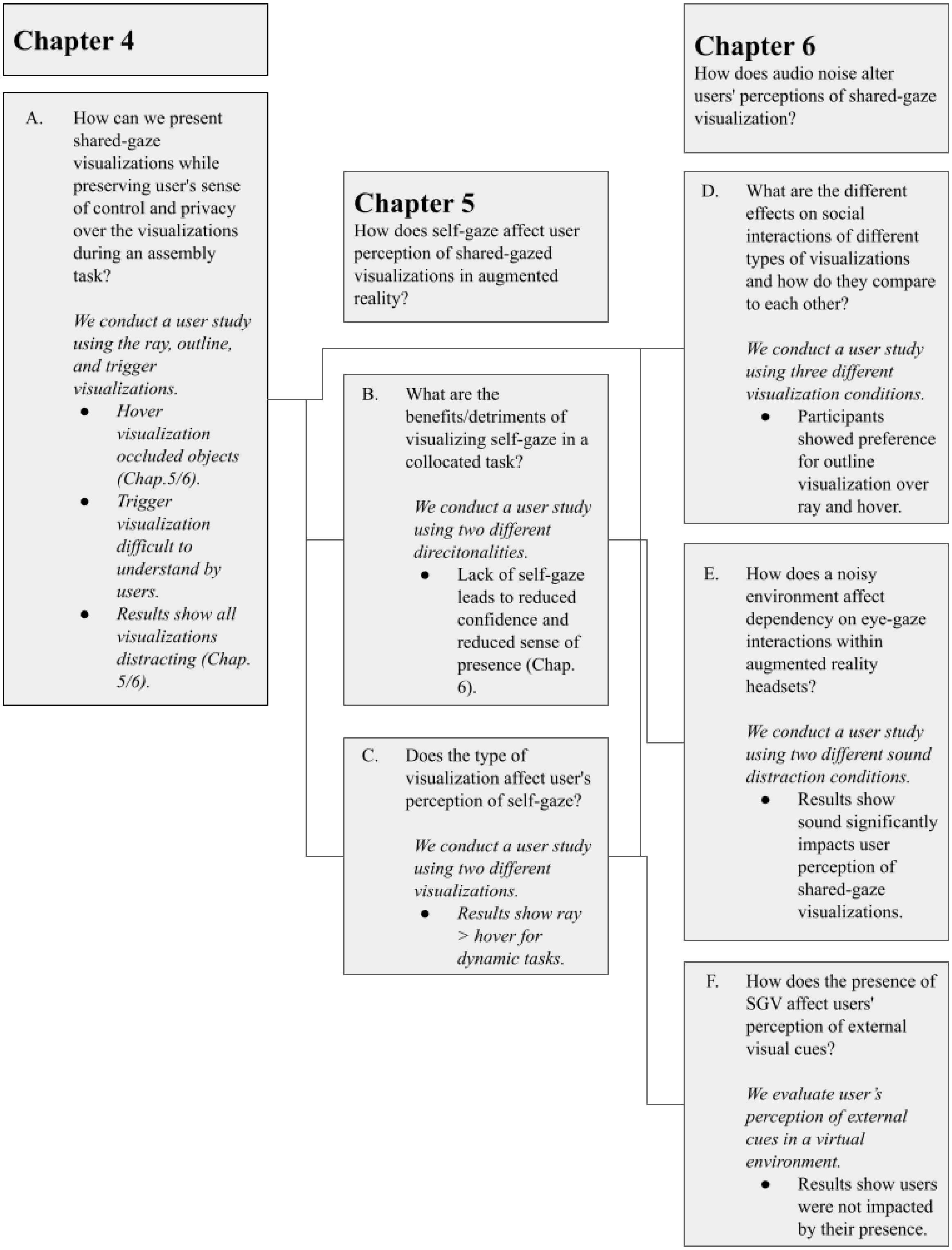


Figure 1-1. Flow diagram of research questions and findings. Subresearch questions are labeled by letters. The research conducted is italicized. Findings are bullet pointed under the research conducted.

CHAPTER 2
BACKGROUND

2.1 Industry 4.0 and Implications

Industry 4.0 refers to the fourth major industrial revolution and the rise of ”smart factories”, which have the capability of self-governance, flexibility, and optimization to increasing customer’s individualized needs [27, 86, 104]. Industry 4.0 is composed of six main principles: modularity, interoperability and interconnection, information transparency, decentralisation and autonomous decisions, real-time capability, technical assistance, and service orientation [86]. From product development to manufacturing technologies, innovative technologies are revolutionizing the entire chain of the production process [42, 162].

Technology has been a main driving force in Industry 4.0 by integrating the Internet of Things with manufacturing tools and creating cyber-physical systems [104, 116]. Components and systems that were once disjointed, can be connected together [86, 104]. For instance, simulated virtual environments on a cloud server can parallel real world environments and can provide support, interventions, and optimize the production chain [86, 161].

Industry 4.0 places a particular emphasis on the integration and enhancement of the human worker via smart tools with the goal of improving their capabilities and productivity [42, 64, 104]. Examples of this phenomenon can be observed through human-robot collaborative systems [40, 46, 47, 150]; maintenance, assembly, and manufacturing guidance systems [19, 46, 50, 55, 70, 89, 150]; and augmented reality systems [21, 50, 63, 145, 184].

2.1.1 Augmented Reality

Industrial augmented reality (IAR) refers to the intersection and development of augmented reality technologies and industrial applications. Augmented reality has been foreshadowed as a driving force for enhancing the future worker [63, 184]. Since its inception, augmented reality devices have been developed for aiding in industrial design [41, 62, 122]. The concept of IAR was first conceived by Boeing in the 90’s with the goal of providing factory workers with diagrams to construct aircraft parts [41, 65].

Today, the concept of providing guided augmented visualizations during complex tasks has become a reality. Due to the inherently noisy nature of industrial environments, augmented reality (AR) offers a unique opportunity to deliver information to workers engaged in precise and complex tasks [202]. AR support has been implemented across various domains, including construction [94, 36], assembly and maintenance [8, 9, 19, 38, 43, 46, 55, 68, 70, 150, 152, 202], occupational safety [32, 60, 75, 76, 78, 93, 172], design [25, 49, 96, 122, 124], and navigational tasks [4, 11, 84, 100, 149, 193]. AR helps improve spatial understanding and representation through 3D visualizations [122, 134]. For instance, in complex maintenance tasks involving intricate parts, AR can enhance the visibility of occluded objects [52, 134]. During guidance tasks, AR devices can provide error correction when a user misses a step [112, 172, 186], and anchor annotations directly over objects to support task execution [169, 202]. Moreover, augmented guidance enables novice workers to complete tasks with minimal prior experience [37, 108, 136, 185].

Augmented reality devices come in a variety of shapes and sizes including handheld, head mounted displays (HMDs), and ambient displays [28, 138]. Each type of device has their own set of advantages and disadvantages depending on the context. For instance, handheld augmented reality devices are hard to use ambidextrously, and may not be the most conducive to use during a task that requires freedom of hands [55, 101, 158]. Ambient displays are hard to implement universally and lack dynamic functionality [13, 113]. HMDs are seen as the more favorable option for augmented reality since they allow worker to visualize information while maintaining freedom of hands and movement [50, 61].

Despite the benefits of AR for industrial settings, most AR research has never really left the lab, and has not been universally adopted by industries [21, 43, 63, 118, 119, 152]. The lack of adoption could be attributed to the technical limitations of devices, such as being too heavy, small field of view, short battery lives, tracking issues, and a lack of usability tests [18, 38, 43]. Based on these limitations, my proposed works will investigate simulating working conditions which includes, noisy [50, 145] and rough environments [145].

2.1.2 Collaborative Augmented Reality

Augmented reality provides a variety of benefits for industrial applications, and collaborative augmented reality further builds upon the same philosophies by extending to multiple operators and creating an immersive mixed reality experience. Through a shared experience, collaborators can interact with multiple angles of visualizations, making it easier to communicate concepts through 3D visualizations [14, 141]. Shared experiences in AR help to improve process skills which include critical thinking, problem solving, and communication during collaborative tasks [54, 163]. In maintenance tasks, AR can provide visual reinforcement to original documentation and provide workers with an idea of potential challenges they will encounter prior to performing a task [179].

Despite the potential for aiding in collaboration, there is a lack of significant literature that proposes a collaborative framework for IAR [163, 179]. Prior work in collaborative AR for industrial settings has mostly looked at remote collaboration from an expert [6, 46, 117, 180], human-to-robot collaboration [5, 40, 46, 47, 150, 157, 166], or the technical aspects of developing a collaborative human-to-human system [179, 199].

Current augmented reality headsets hamper non-verbal communication by covering participants faces or employing visualizations which may occlude collaborators view of each other [146, 148, 160]. Furthermore, little work has looked into the social aspects of augmented reality [57]. Social presence serves as an important factor for interaction and cooperation quality in AR [127, 142]. However, prior work has had a lack of analytical methods for measuring social presence in AR, and has mostly focused on using questionnaires and interview data, which may not be reflective of the actual collaborative interaction [137]. My dissertation work looks into understanding the social effects of augmented information in industrial applications.

2.2 Non-Verbal Communication in Industrial Settings

Nonverbal communication is essential to natural human interaction and takes place through changes in body language, eye-contact, and facial expressions [99, 155, 189]. Specific nonverbal cues are unique to culture and a lack of understanding can lead to conflicts [20, 115, 155].

Additionally, nonverbal communication also be used as a method to signal code switching, being used a cue to signal a formal or informal setting [175].

In noisy and hectic industrial settings, nonverbal communication plays an especially important role in maintaining awareness and coordination among workers [175]. Certain forms of communication, such as verbal interaction, may become ineffective or even obsolete in such environments. For example, in meat processing plants, workers wear earplugs to protect their hearing and instead use hand gestures to convey status updates [175]. In these cases, workers rely on nonverbal cues to overcome communication barriers caused by noise. Such cues offer a seamless and efficient medium for quick communication [20, 82, 140]. Through changes in eye contact, glances, and facial expressions, workers can effectively understand one another [106, 175].

Aside from a few studies looking at non-verbal communication mediated between human workers and robots [10, 157, 166], few works have looked into mediating nonverbal communication in industrial settings for human-to-human interaction through augmented reality headsets.

Eye gaze is a fundamental component of nonverbal communication and works in tandem with other forms of communication, including verbal interaction. Eye contact helps establish shared attention and social connection [99]. For example, avoiding eye contact while someone is speaking may give the impression of disinterest or disregard [99, 189]. As a nonverbal signal, eye gaze influences group decision-making processes [99, 167]. Moreover, eye gaze conveys cues about a person's intentions and can be used to predict decisions based on their gaze direction [2].

Augmented reality (AR) headsets can interrupt natural face-to-face interactions, including eye contact [146, 148, 160]. Additionally, eye contact is not always feasible, as users may be focused on a task and unable to offer their attention at that moment [90, 197, 198]. This occlusion of natural social cues further disrupts collaboration. Social presence is a critical factor influencing the quality of interaction and cooperation in AR environments [127, 142]. Collaborators need to be aware of each other's presence [146] and be able to maintain eye contact and gaze awareness

[16]. Gaze awareness, in particular, has been shown to enhance collaboration, and my dissertation investigates how to improve collocated collaboration through gaze-aware interfaces [198].

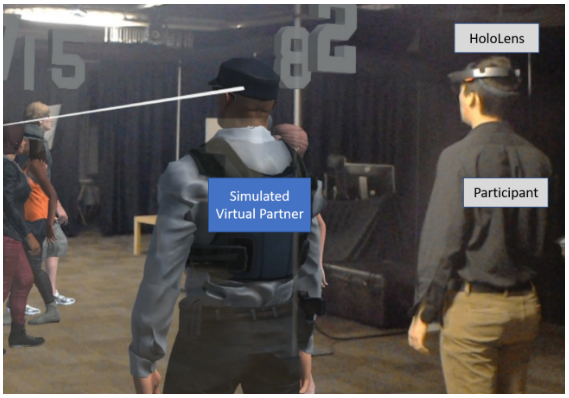
2.3 Shared-Gaze Visualizations in Collocated Augmented Reality

Since the early days of AR, shared-gaze has been utilized as a method for communicating collaborators' attention and focus [15]. However, before eye-tracking was properly integrated into HMDs, prior work used head-tracking estimations to gauge collaborators attention and focus [17], which were not accurate measurements [160, 173]. With the advent of eye-tracking integrated into HMDs, such as the Hololens 2 [176], we can more accurately measure user's attention and provide visualization support.

Shared-gaze has been visualized through gaze rays [22, 33, 58, 59, 90, 111, 132] (Shown in Figure 2-1a), 2D representations [2, 22, 33, 87, 90] (Shown in Figure 2-1b), and 3D representations [31]. While a majority of the visualizations were constant or ”always-on”, a few works investigated dynamic visualizations that changed based on changes user input aside from their current focus. For instance, gaze-triggers [90], alternating visualizations based on detected occlusion [22], and a trailing path [33, 90] (Shown in Figure 2-1d). Compared to static methods of visualizing gaze, dynamic visualizations provide more information on a user's intentions, such as past gaze history [33, 90], a user's orientation [22], and a collaborator's elevated focus [90].

Prior work has evaluated shared-gaze visualizations through a broad range of contexts including search and match [15, 58, 59, 90, 132], spatial coordination [33, 111], navigation [2, 22], design [31], and puzzle tasks [87, 90]. For a target location task, gaze ray was found to significantly improve performance but trailing path was preferred by users [33]. Comparably, for a navigation task, users significantly predict their partner's attention more accurately with shared-gaze than without it [2].

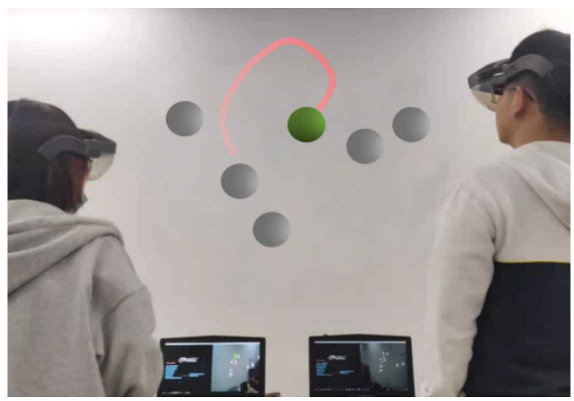
Although, a large number of prior work did not measure the behavioral effects of the visualizations implemented [58, 59, 87, 111, 132], the type of visualization employed has been shown to have a behavioral effect on participants' perception of their collaborative interaction [2]. Shared-gaze cues help users effectively predict a partner's intentions, enhancing normal



(a) An example of the gaze ray visualization can be seen here in practice. However, the user does not have one themselves and observes their virtual partner's visualization [58].

(b) The 2D dot visualization shown here is hovering over the coffee mug. We can early on see how this would be a limitation by blocking the view of the observed object [2].

(c) The cursor donut visualization provides a unique response to the dot visualization. By allowing users to point their eye-gaze direction, they can communicate to their partners where they are focused on, while preserving a view of the object [90].



(d) The 2D trailing visualization provides a medium information not captured by the other visualization types: eye gaze history. By sharing interest history, users can get an idea of how their partner came to that focus point through gaze history [33].

Figure 2-1. Four images showing different variations of shared-gazed visualizations ranging from 2D to 3D implementations.

eye-contact, facilitating joint attention, and aiding in collaborator awareness [2]. However, while gaze-ray found was to improve pair communication with minimal mental workload [90], participants felt more connected with their partner when using a moving trace visualization than gaze-ray [33]. Additionally, gaze-ray was shown to elicit a physical reaction from participants, which suggests it may have been distracting [22].

While shared-gaze visualizations show promise for aiding collaborators in an industrial environments, the study of shared-gaze visualizations with external stimuli remains understudied. Prior work has not utilized shared-gaze visualizations in noisy environments. Most studies have focused on the implementation of shared-gaze in controlled settings with minimal external stimuli. Industrial environments are complex and loud spaces that depend on the use of nonverbal communication [94, 202]. My dissertation work studies how user's perceptions of shared-gaze visualizations are altered during a task with background noise.

Prior work has investigated how users interact with shared-gaze while manipulating or interacting with a task like a puzzle or design. However, they have not combined the use shared-gaze visualizations with physical objects that require attention, such as physical manuals or tools, to complete a task. Physical manuals and tools are present and essential in industrial settings for maintenance, assembly, and manufacturing [38, 68, 134]. My dissertation work investigates how to implement shared-gaze visualizations while users require multiple avenues of attention, such as manuals, their partners, and their collaborative task.

Gaze-triggers provide a unique opportunity for eye-based input. Users can utilize their focus to trigger events if their hands are currently occupied. However, with existing implementations of gaze-triggers, users neglected any noticeable change it had with the visualization [90]. On the other end of the spectrum, users were confused when gaze-visualizations were altered based on contextual changes [22]. Additionally, current implementation of shared-gaze visualizations are "always-on" meaning that users cannot choose when to display visualization. The lack of control of visualizations presents a challenge to users that want to preserve their privacy. By properly communicating the current state of visualizations, users would be able to recognize and understand the behaviors of the visualization.

In regards to the type of task employed to evaluate shared-gaze visualizations, prior work has mostly looked at 2D tasks. Augmented reality provides an advantage of being able to visualize objects that may be behind another and enhance spatial awareness [134]. However, this advantage remains underutilized and understudied. Additionally, the 3D evaluations that were employed, required users to be situated in place [58, 59, 132]. Real world tasks in an industrial settings require workers to have flexibility in their actions. The work I am dissertation will investigate the use of shared-gaze visualizations for dynamic 3D tasks.

Finally, assembly, maintenance, or manufacturing tasks are popular in industrial applications and support for these processes are highly sought after [19, 46, 50, 55, 70, 89, 150]. However, prior work has not investigated how shared-gaze could aid in manual assembly, maintenance, or manufacturing tasks. My dissertation work investigates how shared-gaze could aid collaborators performing complex manual tasks.

CHAPTER 3
IMPLEMENTATION OF AUGMENTED REALITY EVALUATION SYSTEM

In this chapter, we describe the necessary software, hardware and technical requirements to implement the study evaluations presented in Chapters 4, 5, and 6.

The overall system architecture is shown in Figure 3-1. The main system implementation was the same for all studies (Chapter 4-6). The architecture comprised of four parts: the control computer, the network, and the two HoloLens 2 devices [176]. The control computer handled wizard-of-oz commands and was the main researcher tool for recording log files, managing the studies, and collecting qualitative data. The Photon network handled the communication between all of the devices and synced virtual states. The two HoloLens 2 devices were the main interfaces interacted with by participants. The HoloLens 2 provides all of the necessary eye-tracking information to support eye-gaze interactions. The following sections will go deeper into how each device works to support the full architecture.

3.1 Development and Study Computer

All of the study virtual environments were developed on a desktop computer, which was different from the control laptop due to limitations on simulations. The desktop ran on Microsoft Windows 11 Enterprise, and hosted an AMD Ryzen 7 7700X 8-Core Processor [128], 4501 Mhz, 8 Cores, 16 Logical Processors. The computer ran on 16 GB of RAM. Computer graphics were supported by a powerful NVIDIA GeForce RTX 3060 graphics card [133]. The development machine was mainly used for running simulations and piloting. For the actual system architecture, a Lenovo Laptop was used.

The study was conducted using a Lenovo Yoga 720 Laptop. The laptop ran on Microsoft Windows 10 Enterprise. The laptop hosted a modest Intel(R) Core(TM) i7-7700HQ CPU @ 2.80GHz, 2801 Mhz, 4 Cores, and 8 Logical Processors. The laptop had 16 GB of installed physical RAM. The reason the development computer and the study computer were different was because the study only required the computer to run a lightweight Unity application and collect eye-tracking logs.

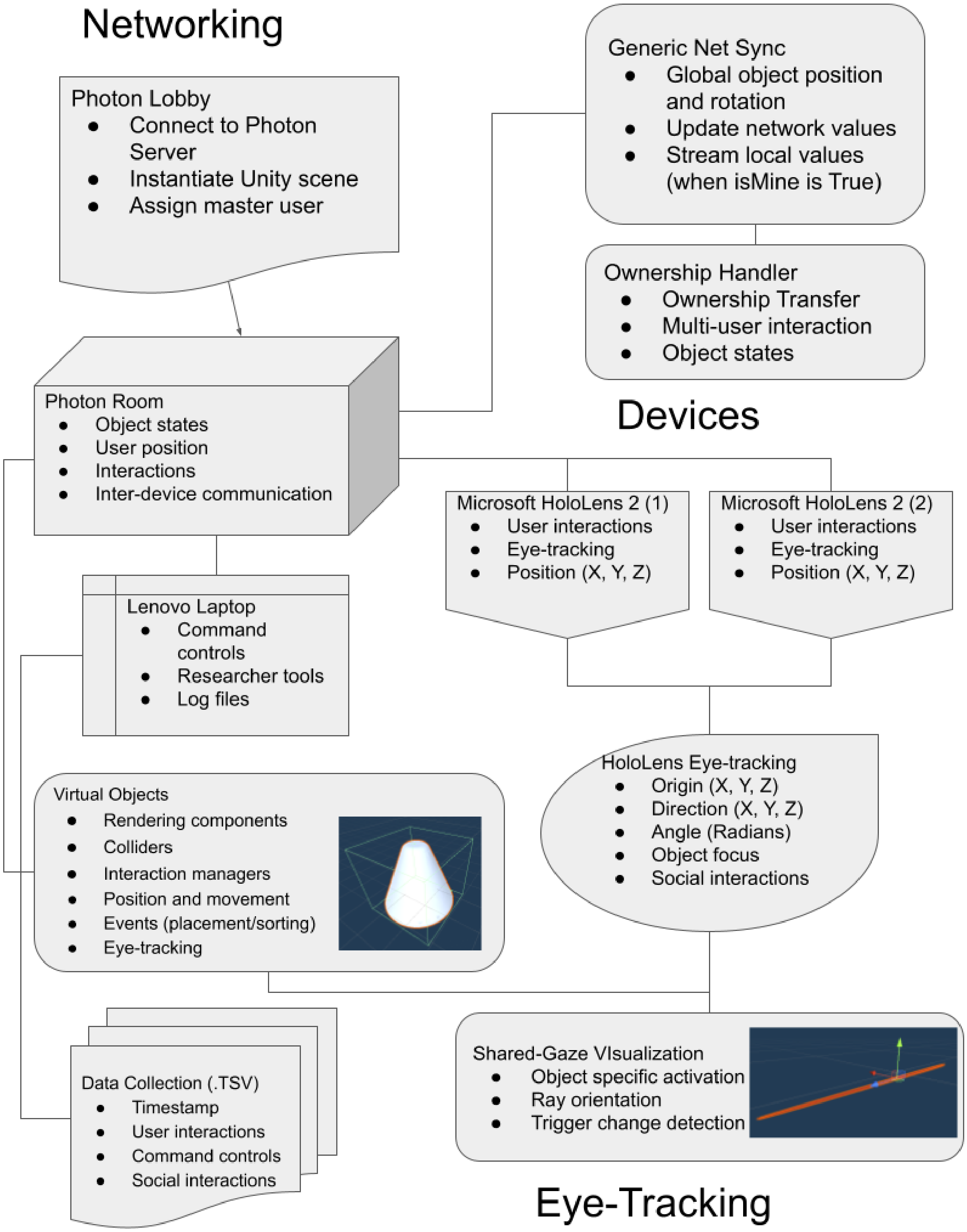


Figure 3-1. System architecture. In this diagram, the essential networking, device, and eye-tracking components are presented. The networking components were necessary for inter-device communication and syncing. The devices provided key features for understanding user interactions, and the eye-tracking support shared-gaze visualizations.

3.2 Augmented Reality Device

The main augmented reality devices used in this dissertation were a set of stock Microsoft HoloLens 2. The HoloLens 2 is an untethered device and boasts up to three hours of active use battery life. For the sake of preserving battery longevity, most of the standby functions were disabled, such as voice recognition and background applications. The HoloLens 2 hosts a powerful Qualcomm Snapdragon 850 Compute Platform chip [26]. Additionally, the HoloLens 2 has a custom-built processing unit for smooth visualizations. The HoloLens 2 is supported by 4 GB of installed RAM. Weighing in at 556 grams, the HoloLens 2 supports a broad range of users with a comfortable lightweight system and one-size-fits-all adjustable sizing. The HoloLens 2 provides a wide field of view at 52 × 35 degrees (diagonal 43°), providing a wide range of design opportunities [176].

A main benefit of the HoloLens 2 is the eye-tracking features it supports. The HoloLens 2 utilizes eye tracking with a sampling rate of 30 Hz and a nominal spatial accuracy of 1.5°, providing gaze data for both eyes simultaneously. This enables developers to create intuitive input and interaction scenarios, allowing the system to recognize user intent and accurately determine which holographic elements to interact with. The eye-tracking data is accessible through an API, delivering gaze origin and direction at approximately 30 FPS.

3.3 IDE and Unity

The virtual environment was developed through Unity [74] with the support of Microsoft Visual Studio using the C# programming language. Unity version 2020.3.24f1 was used due to its support of the Mixed Reality Tool Kit necessary for developing mixed reality applications for the HoloLens 2. Access to Unity was provided by the University through a student account. Using a free Personal Unity account led to denied access to the Unity editor for this specific version of Unity.

timestamp	subject	user	focus	origin	o_x	o_y	o_z	direction	d_x	d_y	d_z
14:44.9	LOCATION	user_Fomyvizha	wall 4	ORIGIN(x,y,z):	-0.01516	0.008033	-0.01733	Direction(x,y,z):	0.019329	-0.17806	0.98383
14:47.1	LOCATION	user_Fomyvizha	floor	ORIGIN(x,y,z):	0.091196	0.140088	0.131889	Direction(x,y,z):	0.385394	-0.33429	0.860073
14:47.2	LOCATION	user_Fomyvizha	paper	ORIGIN(x,y,z):	0.102666	0.130385	0.155643	Direction(x,y,z):	0.342044	-0.44386	0.828248
14:47.2	LOCATION	user_Fomyvizha	wall 4	ORIGIN(x,y,z):	0.10689	0.125448	0.164532	Direction(x,y,z):	0.3335	-0.48192	0.810265
14:47.4	LOCATION	user_Fomyvizha	floor	ORIGIN(x,y,z):	0.169593	-0.01653	0.324708	Direction(x,y,z):	0.531867	-0.69281	0.486965
14:47.6	LOCATION	user_Fomyvizha	metal	ORIGIN(x,y,z):	0.180808	-0.28527	0.443759	Direction(x,y,z):	0.888561	-0.45435	-0.06347
14:47.7	LOCATION	user_Fomyvizha	floor	ORIGIN(x,y,z):	0.174279	-0.39435	0.468907	Direction(x,y,z):	0.868848	-0.33538	-0.36418

Figure 3-2. Example logging snip with timestamp and eye-tracking data points.

3.4 Virtual Environment Development in Unity

3.4.1 Spatial Synchronization

The HoloLens 2 provides strong support for local orientation through its Scene Understanding capabilities. Scene Understanding allows the device to generate a representation of the 3D environment, enabling a wide range of features for handling virtual objects. These features include remembering object placement and orientation, accounting for occlusion by the physical environment, supporting object physics, and facilitating user navigation within the environment. This functionality was further enhanced through the use of spatial anchors.

Azure Spatial Anchors were implemented to synchronize the virtual environment across multiple HoloLens 2 devices using fixed points in the physical space [135]. This cloud-based service enabled persistent placement of holographic content, ensuring that virtual objects appeared in the same physical location for all participants. The implementation involved creating and uploading spatial anchor data to the Azure cloud, establishing reliable anchor sharing between devices with error handling, managing anchor lifetimes and persistence across sessions, and incorporating fallback strategies in cases of anchor retrieval failure. Spatial anchors are saved to disk, allowing the device to reorient itself if orientation is lost. This approach ensured consistent spatial reference points across devices—critical for collaborative tasks and for experimenters observing participant interactions with virtual content.

3.4.2 Physics and Collision

The interactive objects in our studies were implemented with multiple components to ensure realistic and responsive behavior [181]. Each object was equipped with Box Colliders custom-fitted to its geometry to enable accurate collision detection with other virtual objects and the physical environment. For complex shapes, compound colliders were used to optimize performance while maintaining interaction fidelity. These compound colliders were generated from the objects' existing meshes using Unity's Generate Collider functionality during import. Compound colliders were particularly used in the sorting task, where objects had more complex shapes compared to the assembly task, which used simpler, primitive shapes. Unity's physics system was applied to all interactive objects via RigidBody components, enabling gravity, momentum, and natural object behavior. Physics parameters were carefully tuned to balance realism with reliable interactions in the augmented reality context. Specifically, gravity was activated within the RigidBody component, and objects were assigned a simulated mass of 25 and an angular drag of 0.25. The application of gravity and mass ensured that objects did not drift away with minor interactions and reliably fell when users released them.

3.4.3 Manipulation Framework

To enable natural interaction with virtual objects, several Mixed Reality Toolkit 2 (MRTK) components were implemented [114]. The core Object Manipulator component processed HoloLens 2 hand-tracking data, allowing for one and two-handed manipulation gestures such as rotation, scaling, and translation. For direct, close-range interaction, the Near Interaction Grabbable component was added to simulate realistic grasping. These manipulations were initiated using the system's pinch gesture, which supports both left and right-handed users.

To guide user actions and enforce task rules, the Constraint Manager was used to apply several custom constraints. These included limiting object scaling, restricting movement to the defined task space, and automatically disabling interactions once an object was placed in its correct location to prevent accidental displacement. Finally, manipulator settings were fine-tuned to align with each object's collider bounds, providing appropriate visual and haptic feedback during use.

3.4.4 Network Synchronization

To maintain consistent object states across devices, a custom Ownership Handler Script managed object ownership in the networked environment, preventing interaction conflicts when multiple users attempted to manipulate the same object simultaneously [1, 44]. The ownership system incorporated automatic transfer of ownership when objects were grabbed, visual indicators showing current object ownership, smooth transition handling to prevent object state discontinuities, and ownership timeout mechanisms to recover from network interruptions. These technical implementations collectively created a responsive, consistent augmented reality environment that supported natural interactions while maintaining experimental control and data collection capabilities.

3.4.5 Assembly Task

The experiment involved an assembly task where participants built three different structures: a house, a catapult, and an aqueduct. The building components, such as rounded blocks, were based on Unity's primitive shapes. A key technical challenge arose from the object's meshes; a full, detailed mesh was too complex for efficient collision detection (Figure 3-3). Therefore, to optimize performance, we used a simplified box collider for each object instead (Figure 3-4).

Base plates were provided for placing objects. The environment included interactable objects and static objects on the side. Interactable objects disappeared after they collided with the positioning object. When an interactable object disappeared, a static object appeared in its place. This gave users the illusion that the objects were ”snapping” into place. A counter increased each time a user placed an object in the correct spot. For each structure, a copy was implemented in the center of the scene. Participants were given an instruction sheet prior to beginning.

A Unity template of the house is presented in Figure 3-5. The main structure is located in the middle of the image. The dynamic objects are located on the sides.

The catapult is shown in Figure 3-6. Similar to the house scene, the static objects are located in the center of the image. With the dynamic objects located on the sides. The catapult

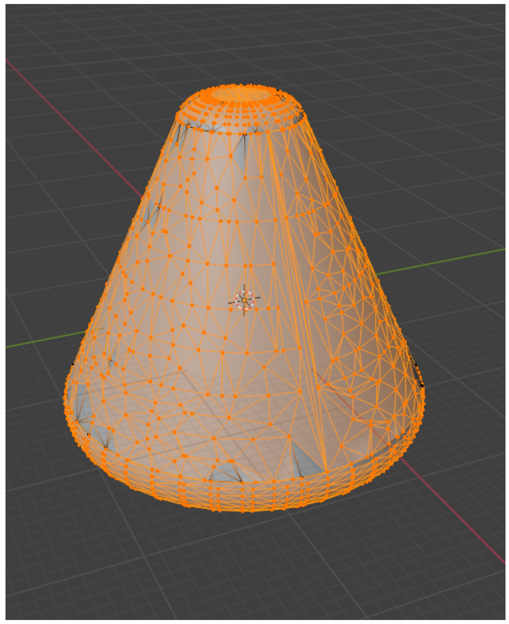


Figure 3-3. Cone object from the assembly task in Blender. Due to the unique shape, adding exact colliders consumes a large amount of CPU performance.

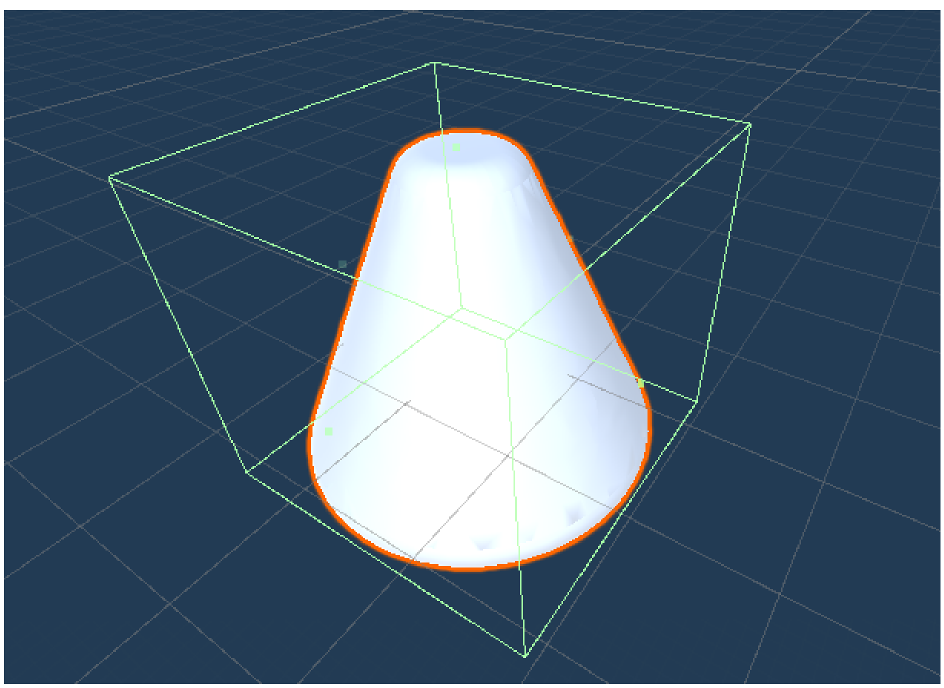


Figure 3-4. Simplified custom collider added to cone. Compared to the original shape presented before in Blender, this approach implements a simple yet effective method of creating interactions with the object.

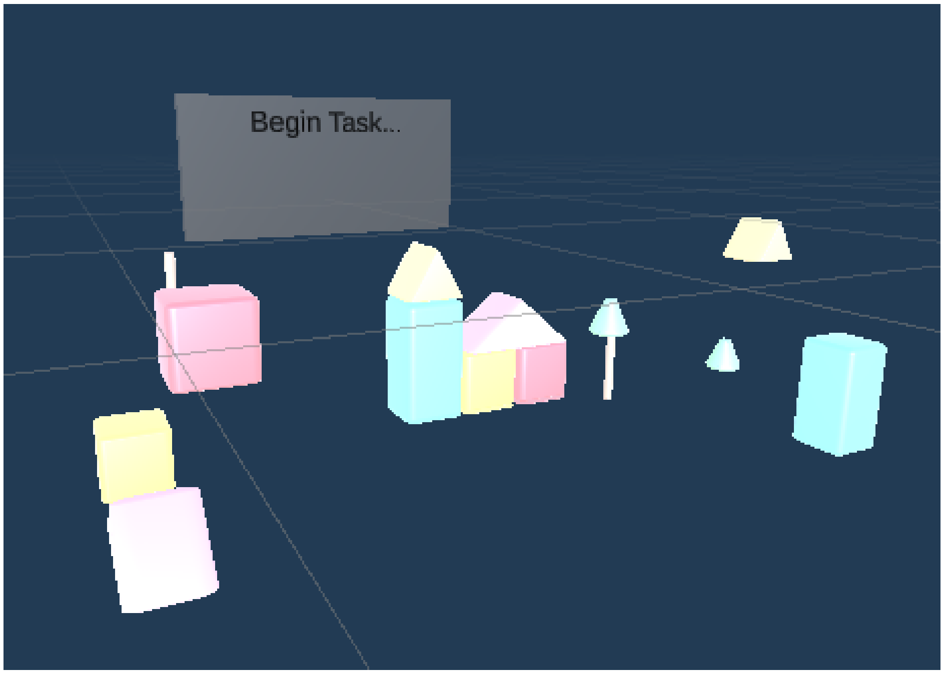


Figure 3-5. Baseline setup of the house task. In the center, can be seen the colliders for the static objects. The dynamic and interactable objects are laying by the side.

object provided a slightly more challenging task compared to previous due to objects being placed within the structure. The aqueduct is shown in Figure 3-7. Similar to both the house and catapult structures, the static objects are placed in the center with the dynamic intertactable objects on the sides.

The scene was controlled by wizard-of-oz commands on the control PC (Lenovo Laptop). Scenes were created by pressing ”1”,”2”, and ”3” on the number pad of the keyboard for the house, catapult, and aqueduct, respectively. Scenes were deleted by pressing ”4” on the keypad.

3.4.6 Sorting Task

The sorting task is a simulation a recycling plant sorting facility. In a real recycling, workers must navigate a dangerous stream of trash to sift through and find recyclable material [191]. This task implements a similar approach requiring users to watch out for dangerous object while sorting through as much trash as possible. Objects are instantiated by the control computer to begin flowing down a designated virtual conveyor belt.

The experimental environment contained a total of 26 virtual objects: 15 pieces of

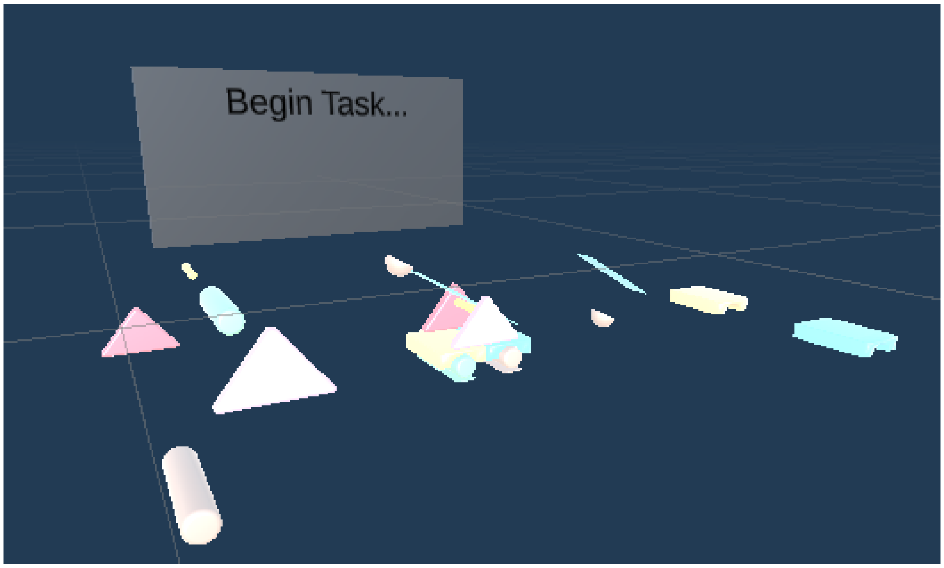


Figure 3-6. Baseline setup of the catapult task. Similar to the house task, the static objects are in the center with the dynamic user interaction objects laying on the sides.

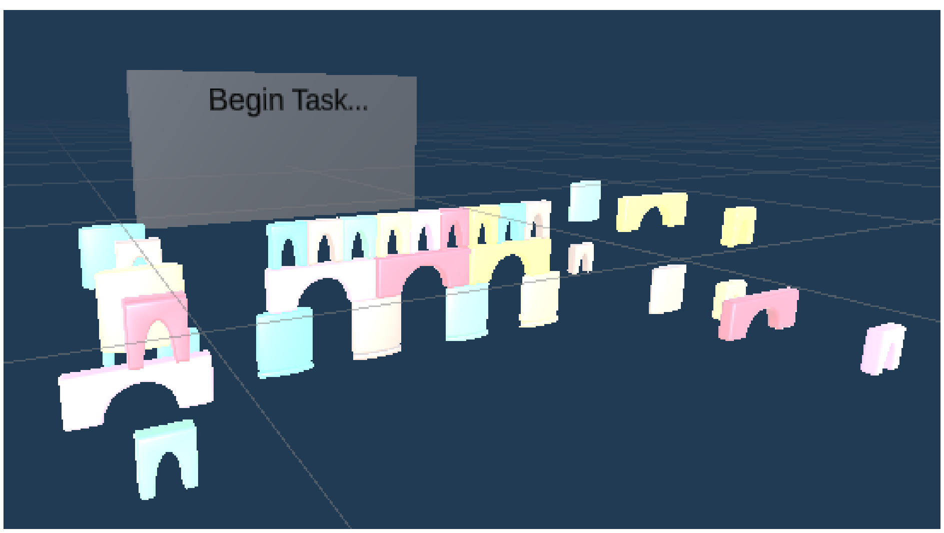


Figure 3-7. Baseline setup of the aqueduct task. Similar to both the catapult and house task, the static objects can be seen in the center, with the dynamic objects on the side.

recyclables, 5 pieces of trash, and 6 dangerous objects on instantiation. The simulated trash was implemented using the Mess Maker Asset by The Quantum Nexus on the Unity asset store [80]. Among the dangerous objects, 80% (or approximately 5 items) were highlighted to indicate their hazardous nature. The object highlight probability was calculated by first setting a Random.Range() from 0.0f to 10.0f, and setting the highlight on for dangerous objects when the value was above 2.0f, so 80% of the time. The color of the object was then set to a translucent red (FF0000) by altering the objects unique Material.

At the beginning of each trial, object positions were randomized within the designated interaction area to prevent learning effects and ensure task variability across participants. When are objects are initialized by the control PC, they are assigned a unique name with their photonView.id. Their position is randomized by calculating a random value using the C# function Random.Range() between -0.5f, 0.5f for their X position and 0.0f, -4.0f for their Z position. The Y position remained uniform for all objects since they remained at the same height on the virtual conveyor belt.

All objects were floor-bound, adhering to physical gravity constraints within the augmented reality environment. The system tracked and counted any objects that fell outside the designated interaction boundaries as ”lost objects” for performance measurement purposes. To maintain system performance and prevent confusion, objects that fell beyond the interaction area were automatically destroyed from the network, ensuring participants couldn’t interact with out-of-bounds items and keeping the experimental area clean and focused. The Unity scene is presented in Figure 3-8.

3.4.6.1 Movement

The movement of objects along the conveyor was simulated using a custom-made script: move.cs. This script implements a simple network-synchronized movement behavior for an object in a Photon-powered multiplayer application. The move class inherits from MonoBehaviourPun to access Photon networking capabilities and moves an object forward along the Z-axis at a controlled rate.

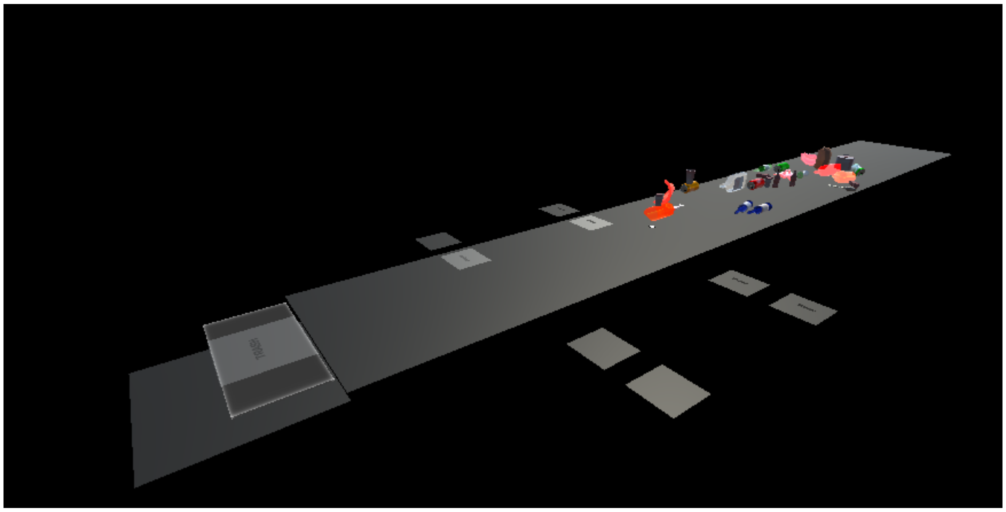


Figure 3-8. Overview of the sorting task. The task appears empty except for the main objects due to the nature of augmented reality, in which the virtual objects are overlaid on the physical world. The recyclable material can be seen at the start of the conveyor, where they are randomly placed.

The key feature of this implementation is its time-controlled movement system. Rather than moving the object every frame (which could result in inconsistent movement speeds on different devices), it uses a fixed interval approach that executes movement precisely every 16 milliseconds. The script initializes by converting the speed value to a smaller scale (dividing by 1000) and obtains a reference to the object's PhotonView component.

During each Update cycle, the script checks if the current client owns the object (pv.IsMine), then verifies if the designated time interval has elapsed since the last movement. If both conditions are met, it moves the object forward by adding a small increment to its Z position and schedules the next movement time. A small thread sleep is included to reduce CPU usage.

3.4.6.2 Sound

Sound in Unity was implemented using the built-in Audio Source component. The sound was attached to users' heads to ensure a consistent auditory experience throughout the task. The exact implementation values are shown in Figure 3-9. A PolyHover sound was used, inspired by ambient noise in industrial environments. This sound is a built-in WAV file located in the MRTK 2 assets at Assets/MRTK/Examples/Demos/Audio/Audio/PolyHover.wav. The PolyHover sound can be described as a continuous drone, similar to the hum of an active air conditioning unit. The sound looped until it was toggled off for all users via the command control system. Volume was kept constant at 0.6 throughout the experience.

3.4.6.3 Wizard-of-Oz Commands

The study employed a comprehensive Wizard-of-Oz interface accessible exclusively through the control PC to manage experiment conditions. Before initiating any commands, researchers needed to verify all devices were properly connected to prevent synchronization issues. The interface featured a series of toggle controls that allowed researchers to activate or deactivate specific gaze-visualizations in real-time. Additional controls enabled researchers to activate specific objects in the scene as needed for different experimental conditions or delete the entire scene to reset the environment. To maintain system stability, the control interface implemented a built-in safety delay of several seconds between commands, preventing rapid-succession inputs that could potentially trigger synchronization bugs or unexpected behavior across the connected HoloLens devices. This command system enabled condition switching during experiments without disrupting participant experience or requiring manual device adjustments.

The assembly and the sorting task command controls mainly differed in the instantiate of objects, but all controls were mostly the same. While the assembly task required the use of ”1”, ”2”, and ”3” for the instantiation of objects in the scene, the sorting task only used the keypad number ”1” for creating objects. Both task used keypad ”4” for deleting objects.

For the control of the shared-gaze visualizations, the keypad was used to toggle on or off. Both sorting and assembly tasks used the same functions. For controlling the activation of ray, hover, outline and trigger, the keys ”O”, ”H”, ”T” (sorting), and ”T” (assembly), respectively.

For sound control (only present in the sorting task), the keypad ”Z” was used to toggle on and off.

3.4.7 Multi-Device Networking

For seamless communication between devices, we developed a multi-player interface using Photo Unity Networking (PUN). PUN is a comprehensive networking solution for Unity games and applications that enables multiplayer functionality without peer-to-peer connections. PUN

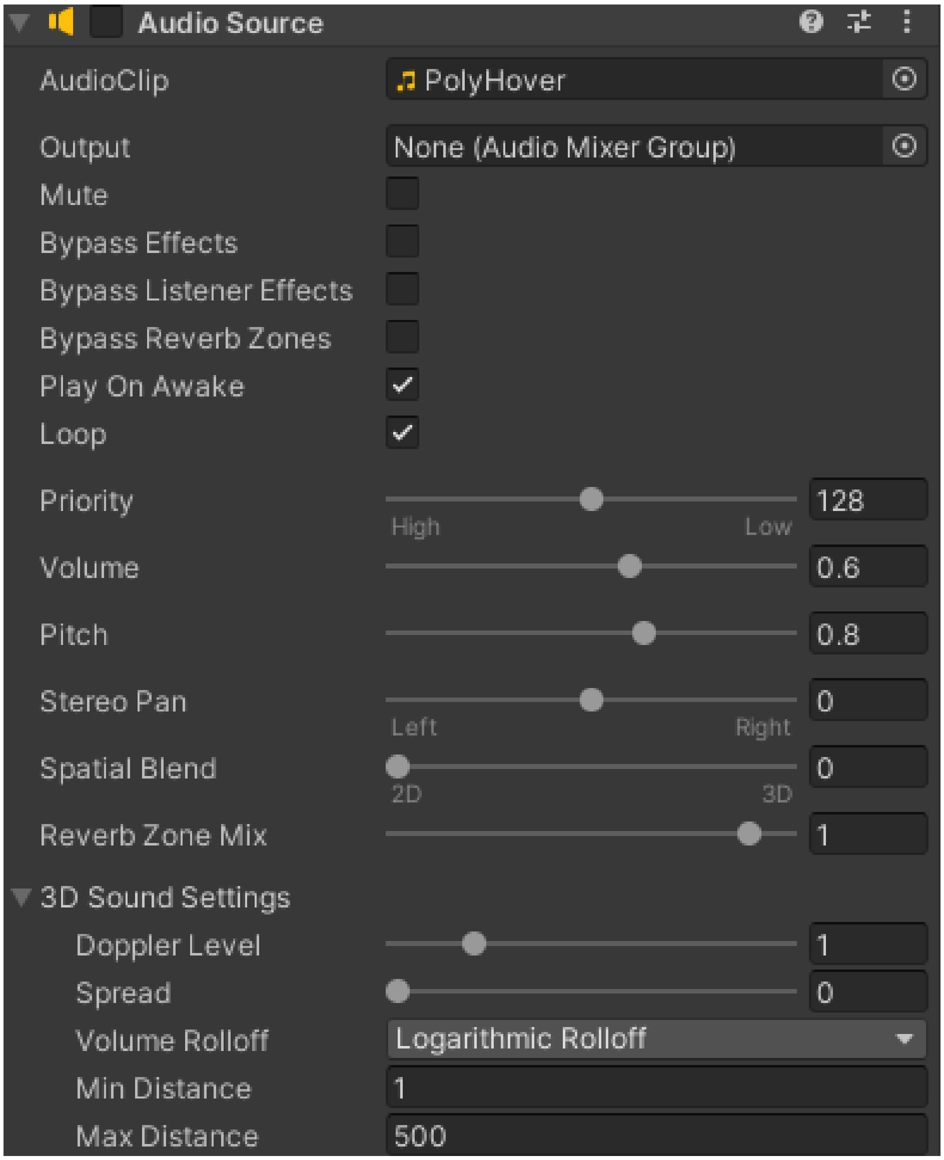


Figure 3-9. A built-in Unity Audio Source component was used to simulate the sound. The following parameters are shown for future replication of the sound created in this experiment.

operates on a client-server architecture where a dedicated Photon server handles communication between players, eliminating the need for direct connections between clients. The system is structured in three layers: the high-level PUN API for Unity-specific features like networked objects and RPCs; the mid-level Realtime API for server communication and matchmaking; and the low-level DLLs handling protocols and serialization.

Connection in PUN begins with PhotonNetwork.ConnectUsingSettings(), which connects to Photon servers using parameters from the PhotonServerSettings asset. The system uses a callback pattern to notify of connection events, with MonoBehaviourPunCallbacks providing an easy way to inherit and override specific networking events.

Game logic in PUN revolves around the PhotonView component, which identifies networked objects and their controlling players. Objects with PhotonViews can synchronize state through an observed component implementing IPunObservable, which defines how position, rotation, and other properties are serialized across the network. For less frequent actions, Remote Procedure Calls (RPCs) allow clients to execute code on specific networked objects across all connected players. Additionally, we used RaiseEvent to send custom data independent from GameObjects.

The following code scripts are modified templates from the original Photon Unity Networking platform.

3.4.7.1 Photon Room

Similar to the Photon Lobby script, this script was extension of the preexisting Photon template script. The PhotonRoom class is a network manager for a multi-user Mixed Reality application built using Photon Unity Networking (PUN). Acting as a singleton, this class handles room management, player instantiation, and synchronized scene loading among connected clients.

The code implements a virtual environment system where users can switch between different interactive scenes (house, aqueduct, catapult, and training) and the sorting scene that are networked across all connected clients. When a player joins a room, the system instantiates their avatar prefab and ensures all players can see each other. The class uses PhotonNetwork's room object instantiation to create shared interactive environments that all connected users can see and interact with.

Key functionality includes keyboard controls to switch between different scenes (numpad keys 1-4) and toggle various interaction modes (hover, trigger, and ”always on” visualization settings) which affect how users interact with virtual objects. These changes are synchronized across all clients using PUN’s RPC (Remote Procedure Call) system. When switching scenes, the currently active scene object is destroyed before instantiating the new one, ensuring all users see the same environment simultaneously.

The code also implements a loading cooldown system to prevent rapid scene switching, waiting 5 seconds between scene transitions. Additionally, it demonstrates proper resource management for Photon, registering prefabs with the PhotonNetwork’s prefab pool to enable their instantiation across the network. The class maintains state about which scene object is currently active and provides parenting functionality to an anchor object, likely for spatial positioning in mixed reality space.

Compared to the original script, the photonroom.cs script received substantial modifications that were required to support the work in this dissertation. Changes include the implementation of command controls (scene changes/instantiations), shared-gaze visualization controls, logger handling, user entry point handling, sound control, and debugging tools.

3.4.7.2 Generic Net Synchronizer

The genericnetsync.cs is also a modified version of the preexisting The GenericNetSync class is a network synchronization component that handles the transmission of position and rotation data across connected clients in a Photon-powered multiplayer application. This script implements IPunObservable and inherits from MonoBehaviourPun, allowing it to serialize transform data through Photon’s network pipeline.

The component has two main operational modes controlled by the isUser flag: user representation mode and standard object synchronization mode. When attached to a user representation object (isUser is true), it continuously updates the transform to match the local camera position and rotation, effectively making the networked avatar follow the user’s head movements in a mixed reality environment. For the local user, it also stores a reference to the PhotonView in the GenericNetworkManager for easy access elsewhere in the application. Non-user objects simply synchronize their positions and rotations with data received from the network.

The synchronization happens through the OnPhotonSerializeView method, which writes the object's local position and rotation to the network stream when this client owns the object, and reads these values from the network when another client is the owner. In the Update method, objects not owned by the local client (where photonView.IsMine is false) have their transforms updated to match the position and rotation values received from the network. This creates the illusion that all clients are seeing the same movements of objects and users across the shared virtual space, despite each client running their own local instance of the application.

Changes from the original code include changes to streaming information (user position/rotation), eye-tracking communication (position/rotation), object specific networking, handling photon of view information, and implementing object ownership.

3.5 Eye-tracking

We leveraged the built-in eye-tracking hardware of the HoloLens 2, building our application on the Mixed Reality Toolkit 2 (MRTK2) eye-tracking tools. Rather than polling at a fixed frequency, eye-tracking events were recorded in the log file only when changes occurred, optimizing our data collection.

For visualizing the gaze ray in front of the user, we applied what may seem like an unintuitive technique for positioning and rotation. While Unity typically works with local transformations, our approach focused on achieving accurate global positioning. First, we obtained the gaze direction vector from the eye-tracking input system. Then, we determined the origin point (the user's eye position) from the same input source.

To calculate the proper position for our visualization, we summed the direction and origin vectors, which placed our visual indicator exactly one unit along the user's gaze ray. This calculated global position was then assigned to the transform of our ray visualization object.

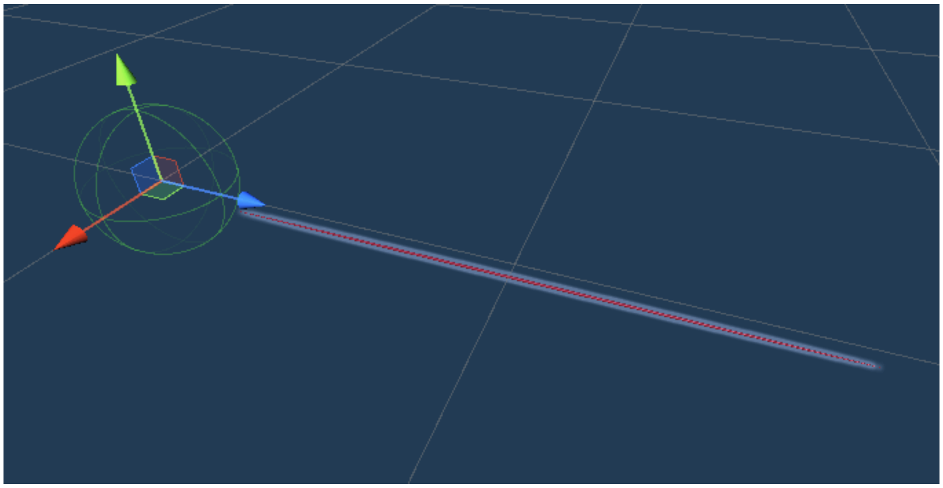


Figure 3-10. Sphere head colliders for detecting eye-tracking events. The gaze ray is shown besides to visualize the ratio of size (1 meter). The collider surrounds the relative area of the user's head (0.2 meters).

Finally, we applied the appropriate rotation by using Unity's Quaternion.LookRotation function with the direction vector as input, ensuring the visualization was properly oriented along the gaze direction.

This approach provided an elegant solution for accurately positioning and orienting our gaze ray visualization in 3D space. A snippet of the code in C# is presented in Appendix A.

3.5.1 Data Collection

Eye-tracking provides researchers with the opportunity to analyze social phenomena without disrupting cohesion. We employ eye-tracking tools to handle events in social communication such as eye-contact, shared focus, and glancing at partner. For each user in the virtual environment, an invisible collider sphere [74] is implemented on the head region to catch eye-gaze instances from their partner (Shown in Figure 3-10). The size of the sphere collider was 0.2 meters in diameter.

Eye-tracking in the MRTK2 works by providing raw useful information such as gaze direction and origin. Additionally, eye-tracking within the framework utilizes colliders to detect object collision. Meaning we can use eye-gaze collisions to detect what object we are looking at, providing us with the name of the object. Assuming we give each object a unique name, we can determine exactly where a user's gaze is focusing on. With this in mind, we implement the object specific shared-gaze visualizations mentioned later (hover, outline). Additionally, we can also extend our eye-gaze interests and record an account of each into the log file (Shown in the 'Focus' column in Figure 3-2). Understanding the method, we can use the invisible collider attached to user's head to collect valuable and useful data on social interactions.

Eye-contact is an essential social communication cue that provides a deep look into a natural phenomena. We collected eye contact information by detecting when a user's eye-gaze collides with their partner's head collider, and vice versa. When a user looked at a partner, but they were not reciprocated, we collected this as glancing at partner. Using the unique id assigned to each participant, we could match with certainty where a user was looking.

Additionally, we collected each unique a user looked at through a task. For example, if a user and their partner were both looking at "RedObject101", using overlaps in their timestamps, we could associate when they were sharing focus.

For all of the described eye-tracking metrics collected, we attained both instances and time. Where instances is the number of discrete events in which a user engaging in the interaction. While time was the amount of time spent in the interaction. These two differ in what they tell us about a user's experience. For instance, a high count of instances, but short time duration, suggests a distracting element. However, more information (such as a feedback survey) is needed to make a well educated assumption [99].

All of the information collected by eye-tracking metrics was synchronized, timestamped, and logged onto a .tsv file.

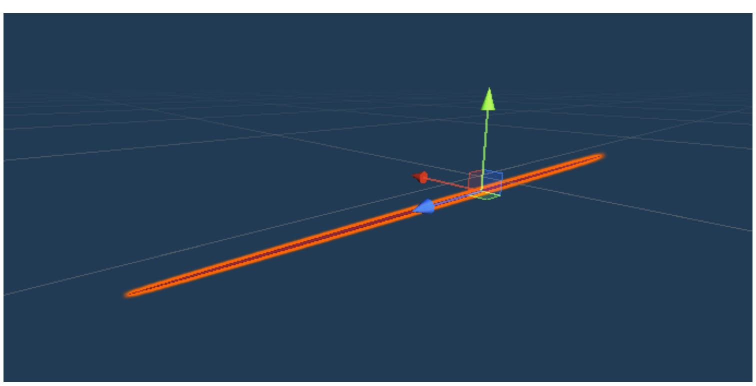


Figure 3-11. Implementation of ray visualization in Unity. The ray visualization was one meter long. The ray was colored red and less than one inch in diameter.

3.5.1.1 Task Logging

The study employed a logging script to collect user interactions in the study, command control sequences, task scoring, and study events. With each log entry, there is an associated timestamp and subject value. Data in the log file was updated on-change, meaning events were only recorded if something within the scene changed. The main feature of the log file was collecting eye-tracking data, which was also collected on-change. For each eye-tracking data point, we collected the timestamp, subject, user name, name of the object, origin position of the gaze (x,y,z), and the direction of the gaze (x,y,z). Each log file ranged from 450-750 KB in size. The log file was saved in a .tsv file format (e.g., 2025-01-31_17-44-20-eye-log.tsv). The logfiles were saved in the respective computer being used at the time. For the user evaluations, they were saved on the laptop PC.

The automated logging system was designed to capture comprehensive metrics regarding participant performance. The system maintained an ongoing count of successful interactions, including correctly sorted items and properly handled recyclables, providing quantitative data on task completion accuracy. Additionally, the system specifically tracked interactions with dangerous objects. These metrics collectively provided a multidimensional assessment of participant performance, allowing us to analyze not only task completion but also the quality and safety of the interaction process. All logged events were timestamped and associated with specific object identifiers to facilitate detailed post-experiment analysis and correlation with eye-tracking data.

3.5.1.2 Data Analysis

While collecting large amounts of eye-tracking data was useful, even more important is understanding what exactly is going on. To analyze eye-tracking logging data from over 40 participants, we developed an automatic script to parse through the data by condition and provide us with eye-contact, shared focus, and glances at partner instances and time.

Each logged file was first divided and labeled by their appropriate condition orders. Then a five-minute cut-off was added for each condition, as each study lasted five minutes. Following the

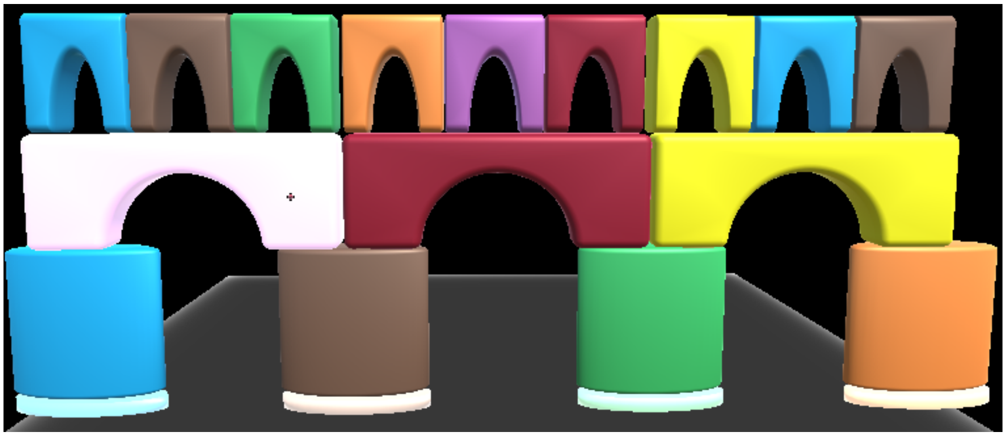


Figure 3-12. Hover visualization in task. Here the hover visualization can be seen shining the left most object in the center. The saturated color allows it stand out in comparison with the objects around it.

time division, the log file was filtered to only contain user eye-tracking data.

The methods for calculating eye-contact, shared focus, and glances at partner were all fairly similar. We used the Pandas [120] tool "pd.merge_asof" to find intercepts within the timestamp data. For eye-contact, we searched for instances where both users were looking at someone. Since there were only two users in the study, we could safely assume they were looking at their partner towards the head region. If more than two people were present, we could have used a unique identifier for user labeling.

After detecting the intercepts of eye-contact, we counted the number of unique instances, giving us eye-contact instances. Finding time was a bit trickier. We found time similarly by identifying the intercepts and then determining how long until one user went out of focus with the other. For example, if two users made eye-contact at 20 seconds, then one user looked away at 25 seconds but the other was still looking at them until 28 seconds, we would count the total eye-contact time as 5 seconds.

Glances at partner is therefore also a product of eye-contact. Given the example mentioned before, we would count glances at partner as a byproduct of an eye-contact instance with the total in that scenario being 8 seconds.

We used a similar approach for shared focus, except instead of looking for interactions in

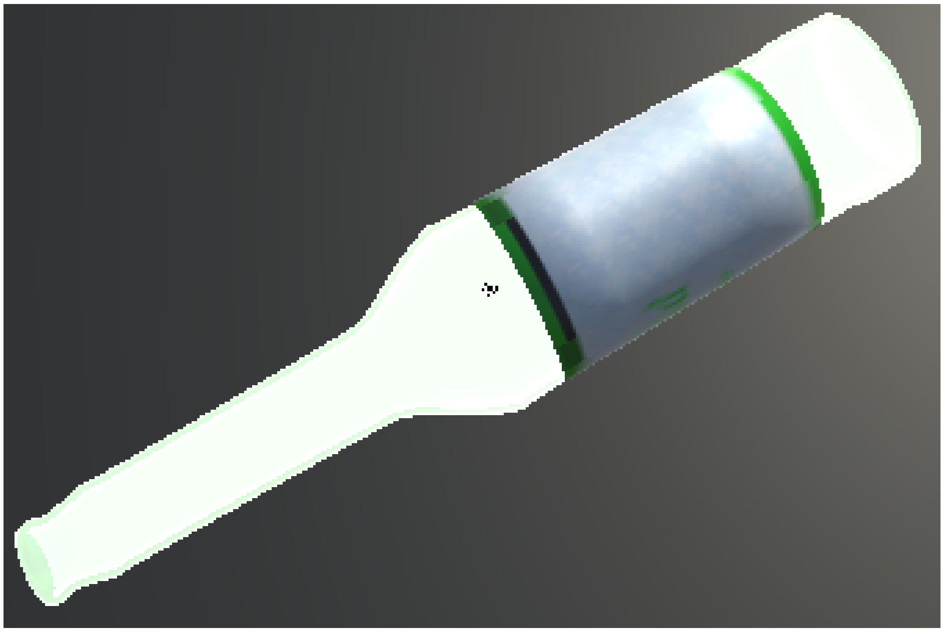


Figure 3-13. Example of hover visualization within the Unity development platform. The object's material is altered to shine the bright color.

Figure 3-14. Unaltered bottle example for hover visualization. Example of what the same bottle looked like before. Note how different the color is to the hover activated version.

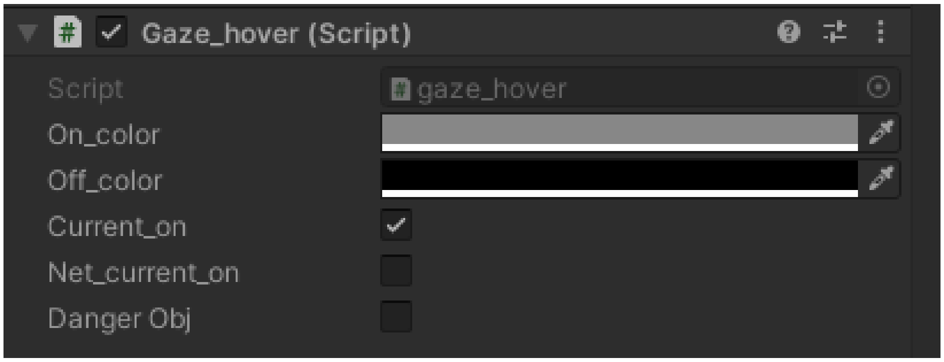


Figure 3-15. The hover visualization utilized a "local-on" and "network-on". The discrepancies in communication was attributed to ownership of objects and their universal states.

which users were looking at their partner, we matched intercepts in objects. We counted instances and duration spent in a shared focus.

Due to nuances in eye-tracking behavior, a tolerance window of 0.7 seconds was applied to account for natural latency in human attention shifts when determining synchronized focus. Finally, all of the information attained from the eye-tracking metrics was saved into a .csv file for later statistical analysis.

3.5.2 Shared-Gaze Visualizations

Across this dissertation, four unique shared-gaze visualizations are implemented: ray, hover, trigger, and outline. As will be further explained in this section, ray and trigger both used direct eye-gaze input information, such as gaze direction and origin, to visualize the interactions. While hover and outline utilized colliders to activate based on user's interactions.

The ray visualization was based on line visualizations in prior work [23, 90]. The visualization was created using a Unity Sphere Primitive shape and sizing it to appear as a line. The ray was attached to the user object in the Unity as a child object. The main user object contains controls for the positioning of the ray visualization. The ray was one meter and had a solid red color (Shown in Figure 3-11).

The trigger visualization used the same design as the ray visualization. The main difference between the two being the method in which the trigger visualization is activated. The trigger visualization would activate on a 1.5 second focus time. The timer would reset whenever a

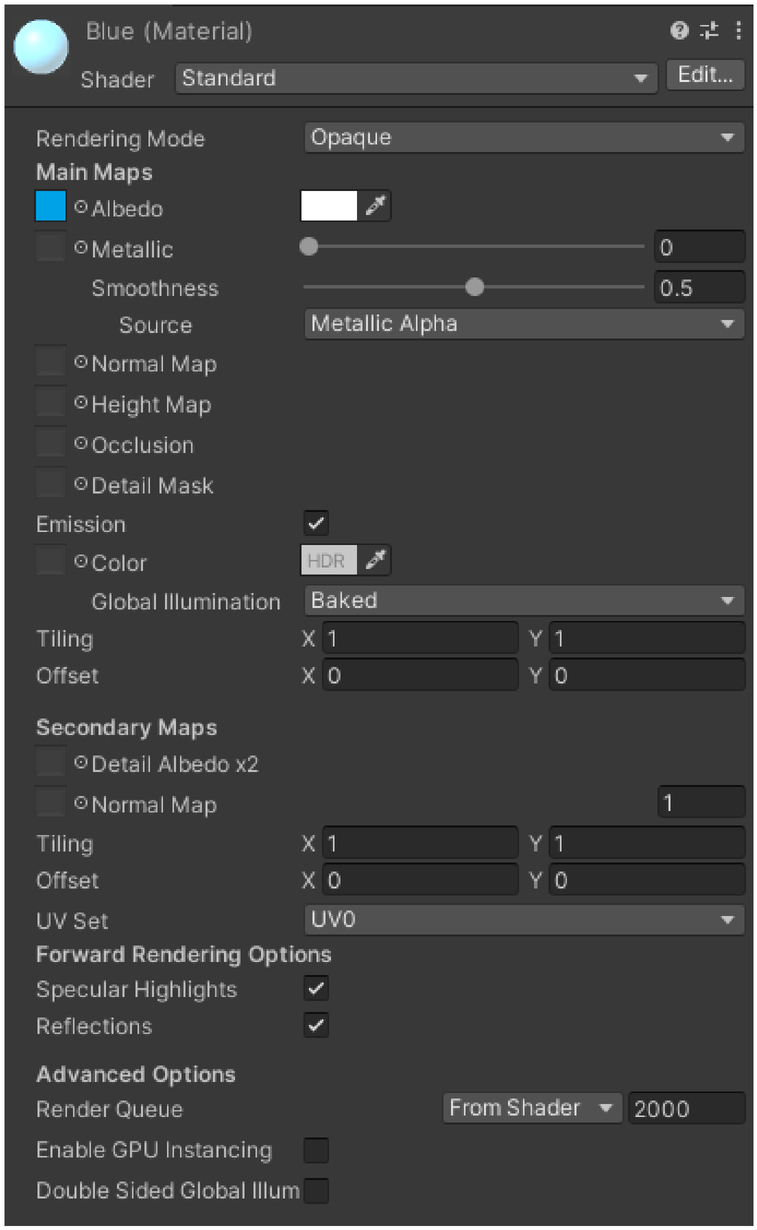


Figure 3-16. Custom material using a preexisting Unity material. The material was altered to support emission and dynamic changes. These changes were essential for supporting the hover visualization. Each object had a unique material. Sharing materials between objects led to multiple objects being altered at the same time.

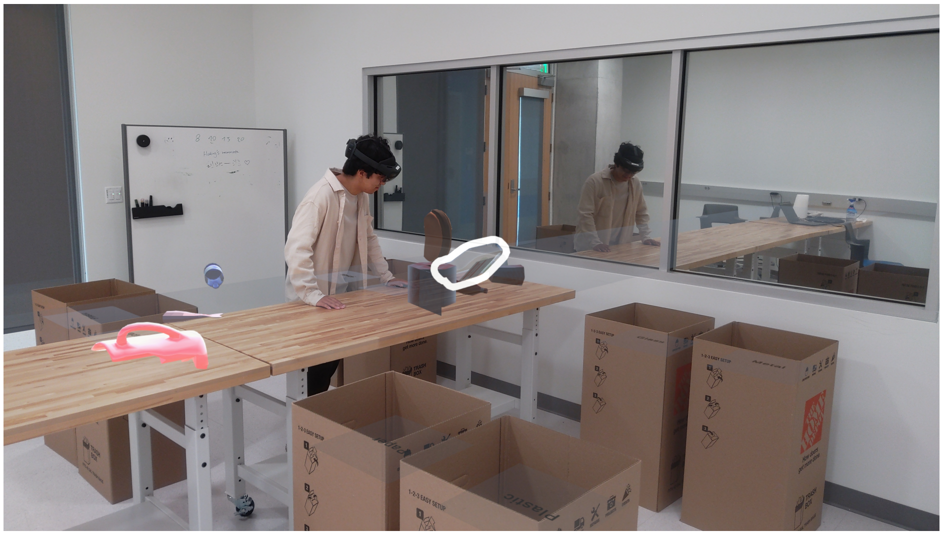


Figure 3-17. Outline visualization over a bottle. Here the outline visualization can seen over the bottle object. The outline users to still see the object, in contrast with the hover visualization. Photo courtesy of author.

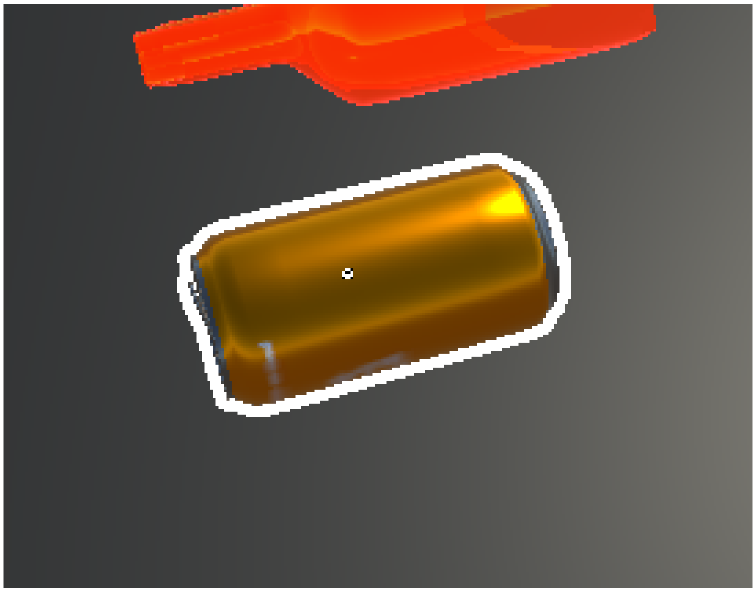


Figure 3-18. Outline visualization over a can. The outline visualization is presented surrounding the can up close. The shape of the outline changes based on a user's geometric orientation around the object they are looking at.

participant altered their view by 1.8 radians. The angle difference was calculated by determining the current and last look direction using the Unity Quaternion.LookRotation() function.

The hover and outline visualization both used the object collision detection provider from the MRTK2 SDK. Based on gaze collisions, we could detect which object was being observed. From there, we could send an PUN event to announce to the object to activate its hover or outline visualization. Multi-device networking ensured the visualization would be visible for everyone.

The hover visualization was implemented by altering the object's material (Shown in Figure 3-12 in the assembly task, and in 3-13 in the sorting task). A custom material was developed to change between a highlight material and a regular state object. The settings for the custom material are shown in Figure 3-16. To activate the highlight property in the material, the emission was enabled. An example of the activated hover visualization settings is demonstrated in Figure 3-15. We specifically altered the objects saturation hue to glow (in contrast to the off mode shown in Figure 3-14). This made the object's color shine bright compared to the surrounding objects. We will see later one why this is a limitation in Chapters 4 and 5. An example of how an object's material was altered is presented in Figure 3-13 and 3-14.

The outline visualization was implemented outline similarly to the hover visualization (Shown in Figure 3-17). The goal of the outline visualization was to allow users to only visualize objects in the scene that were relevant to the context. Using the gaze collider input to detect the object we are looking at, we can communicate with the object to activate their visualization. We

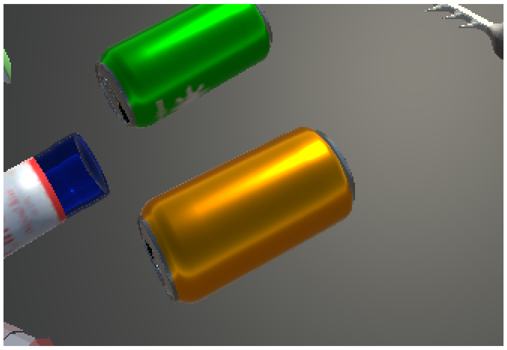


Figure 3-19. Original can presentation without outline visualization. The same can from the outline activated visualization before. Except with the outline off in contrast.

implemented the Quick Outline asset from the Unity store created by Chris Nolet [131]. Similar to the hover implementation, we used the object id to communicate and activate the visualization across the network for all users. The outline was set to a max width value of 10 and max white color value (FFFFFF). An example of what an object looks like when the outline is activated is presented in Figure 3-18 and 3-19.

3.6 Summary

We implemented an augmented reality system to evaluate collaborative interactions using shared-gaze visualizations within a simulated virtual assembly and sorting task. The setup included a control PC and two HoloLens 2 head-mounted displays. The virtual environment was primarily developed using Unity and the Microsoft Mixed Reality Toolkit 2. Virtual task scenes incorporated scripts to manage user interactions, enable networking between devices, and provide researchers with a simple control interface. The HoloLens 2 served as the primary eye-tracking interface, with data collected on the control computers. Shared-gaze visualizations were generated using eye-tracking data and dynamically oriented based on user states. The system described here forms the technical foundation for the research presented in the following chapters. In Chapter 4, we evaluate shared-gaze visualizations for virtual assembly tasks, using the assembly task introduced in this chapter.

CHAPTER 4
EVALUATION OF SHARED-GAZE VISUALIZATIONS FOR VIRTUAL ASSEMBLY TASKS

4.1 Motivation

As mentioned in Chapter 2, the advent of commercial augmented reality devices has led to a rise in the use of mixed-reality technologies to facilitate group work. Augmented reality devices can overcome the limitations of situated displays by allowing collaborators to interact with virtual content while still viewing the real world, resulting in increased user engagement [12]. However, head-mounted displays—one common form of AR device—often occlude eye contact between collaborators. Moreover, during collaborative tasks, eye contact may not always be possible, as collaborators may be focused on the task at hand [198].

Eye contact is a fundamental human trait that is essential to social and group interactions. Observed changes in eye movements between members provides an influential non-verbal cue that affects the decisions that are made [167] and allows collaborators to gauge each others' intentions [71]. Thus, there is a need for developing gaze-visualization techniques for collaborators working with head-mounted displays [198].

Prior work has visualized gaze in augmented reality headsets [33, 90] and shared displays [198]. Gaze visualizations have been used for observing the impacts of virtual gaze cues on face-to-face interactions [90], focusing multi-user attention to similar looking objects [33], communicating cues to collaborators [178, 198], and asymmetric collocated interactions [87]. Despite the substantial progress in developing gaze visualizations, prior methods suffer from lack of control [87, 90, 178], balancing performance and user preferences [33], and privacy issues [198].

Based on the existing limitations of shared-gaze visualizations in augmented reality, we aim to answer the following research question: ***How can we present shared-gaze visualizations while preserving the user's sense of control and privacy during an assembly task?***

To address this question, we conducted a study with eleven participants and found that users exhibited mixed preferences regarding the shared-gaze visualizations. These preferences varied depending on participants' priorities during the assembly task. Drawing from our findings, we conclude with design recommendations for developing shared-gaze visualizations in augmented reality headsets.

4.2 System Design

As mentioned in Chapter 3, two Microsoft Hololens 2 with a 50-degree field of view and a 75 Hz rate were used for the head-mounted displays. The Hololens were synchronized to the room by starting the Unity application in the same physical location. Additionally, Microsoft Azure spatial markers were used to communicate spatial information across the Hololens devices.

A virtual assembly task was conceptualized and developed using Unity 3D engine. Details about the virtual assembly task are presented in the evaluation section. The application communicates the positions and actions of both collaborators. Microsoft's mixed reality toolkit was used for eye-tracking and hand-gesture recognition. The application allowed users to pickup virtual objects by making a pinch gesture.

We implemented three methods for visualizing gaze to collaborators: *constant ray*, *gaze trigger*, and *gaze hover*.

- The *constant ray* condition projects a ray (shown in Figure 4-1) from the headset to the point in space the user is currently focusing on.
- The *gaze trigger* shares the same ray visualization as the constant ray. However, with gaze trigger, the ray is only displayed if a user focuses on a point in space longer than a set threshold. For our study, a threshold of 1.7 seconds was selected based on piloting. Once a user looks away, the gaze trigger is turned off, and the timer is reset (While the dynamics of the trigger cannot be shown in a static format, the visualization that appears after triggering the visualization is the same as the gaze ray shown in Figure 4-1).
- The *gaze hover* does not display a ray but instead highlights objects a user is currently looking at. When a user gazes at an object, the color of the virtual object is saturated causing it to stand out from other objects (shown in Figure 4-3).

4.3 Evaluation

Eleven participants (6 male, 4 female, 1 Non-binary) were recruited from a local university campus and ranged between the ages of 19-27 (Mean = 23.45, Std. Dev. = 2.71). The study protocol was approved by our local Institutional Review Board (Protocol Number IRB202301189).

Figure 4-1. Point of view of the gaze ray. We can see both our own ray extending from our view and the other collaborator's ray. Photo courtesy of author.

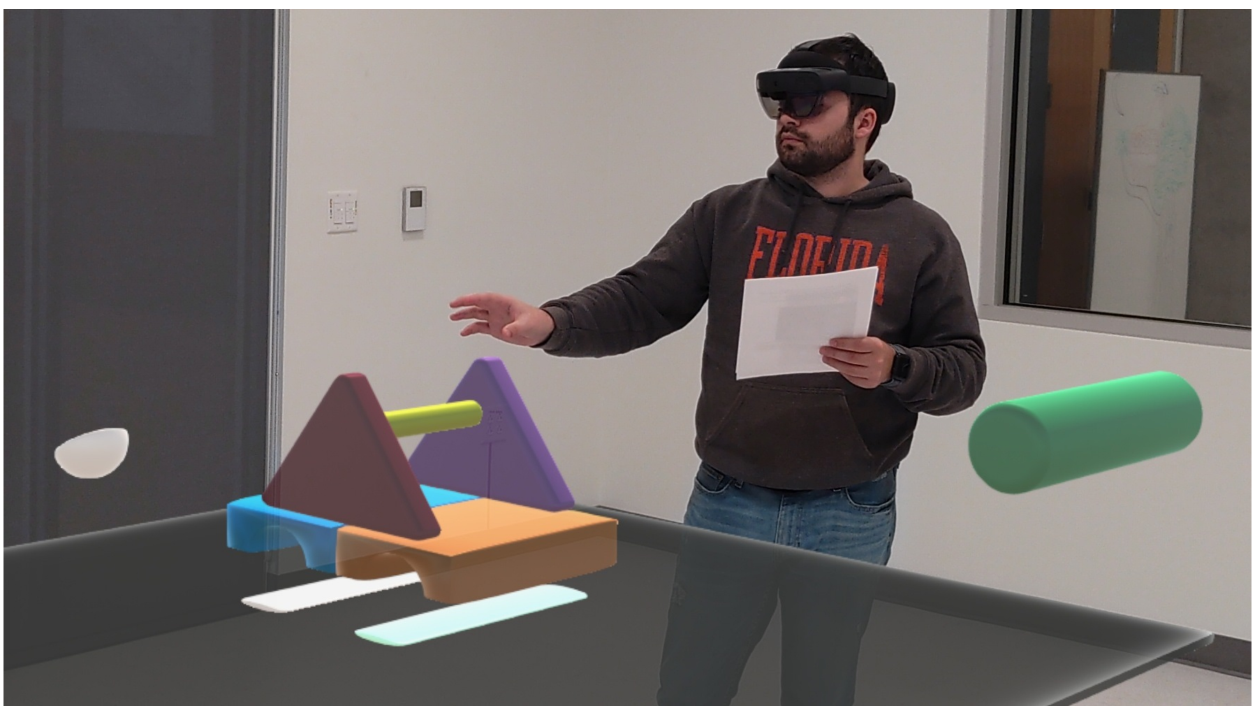


Figure 4-2. User interacting with catapult scene. A view of a collaborator manipulating an object and highlighting it using the gaze hover visualization. The half circle can be seen on the left with a brighter hue than the other objects around it. Photo courtesy of author.

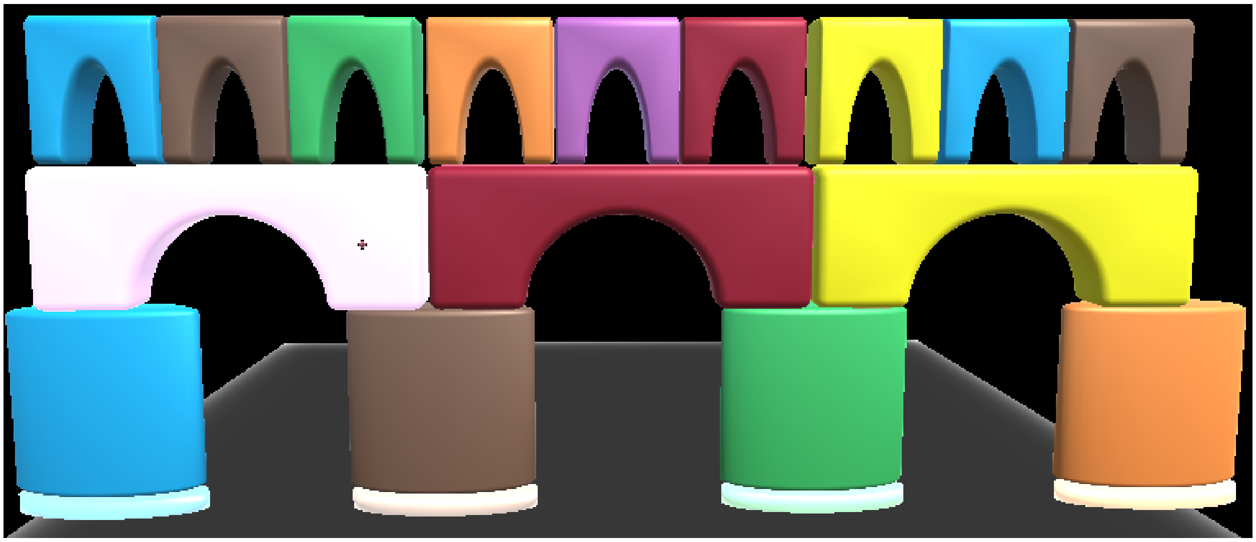


Figure 4-3. Aqueduct object being altered by hover visualization. In this image, we can observe how the gaze-hover highlights an object and makes it stand out with other objects it is next to. We can also observe how it occludes the original color of the object.

The user evaluation consisted of a within-subjects study consisting of two participants working together to complete three assembly tasks while using one of the three eye gaze visualizations. The order of visualizations was counterbalanced using a Latin Square. In the first task, participants were asked to build a simple house (Figure 4-1). The second task was to build a catapult, shown in Figure 4-2. Finally, the last task was to build an aqueduct (Figure 4-3). Different colors were used to represent the various components of the structures. The task became increasingly complex as the study progressed due to the growing number of objects involved in the assembly task. Since the conditions were counterbalanced using Latin squares, we could observe how users' perceptions were affected across all three different difficulty levels evenly.

An assembly task was chosen because it allows for objects to be occluded in a 3D space, in contrast to prior work that investigated the effectiveness of gaze visualizations through 2D tasks [87, 90, 178]. Additionally, assembly tasks are complex and require users to search for items and orient them while aiming to maintain awareness of each others' physical presence. After completing each assembly task, participants were asked to complete a survey based on prior work [90] (Shown in Table 4-1). At the end of the study, participants ranked the conditions and provided an explanation for their choices.

Table 4-1. Collaboration Experience survey questions [90].

Question No.	Survey Element
Intentions	
Q1	”My intentions are accurately represented”
Q2	”My partners intentions are accurately represented to me”
Q3	”I can understand my partners’ focus with ease”
Focus	
Q4	”It is better for me to understand my partner’s focus”
Q5	”It is better for my partner to understand my focus”
Attention	
Q6	”It is easy to observe my partner’s attention”
Q7	”It is easy for my partner to observe my attention”
Reaction	
Q8	”I react to my partner frequently”
Q9	”My partner reacts to me frequently”
Interaction	
Q10	”This form of visualization is effective”
Q11	”This form of visualization is engaging”

4.4 Results

We did not find any significant difference in the survey results between the control (constant ray) conditions and the alternate conditions (gaze hover, gaze trigger). For Q2, participants reported the gaze-hover as being a less of an accurate representation of their partner’s intentions than the other two conditions. A further look into the visualization comparison and feedback survey showed mixed opinions. For instance, one participant appreciated the constant ray and remarked on how the gaze-hover made it difficult to focus on the color of the objects. Alternatively, despite rating the gaze hover as a less accurate representation of their partner’s intentions, P5 enjoyed how the ”[gaze hover] was intuitive, and responded to the thing I was looking at...” and ranked it as their preferred visualization method. For questions Q6 and Q7, participants rated the gaze trigger as being a more difficult method of observing each other’s attention compared to the other conditions. We saw a common trend of participants finding the trigger to be distracting. For example, P3 found the other two conditions ”faster and more efficient” since they didn’t have to wait for the visualization to respond. Additionally, P7 appreciated the other two conditions because they were ”more intuitive.” For Q8, participants rated gaze hover and gaze trigger as having less of an effect on their reactions to other participants compared to the control condition. We can gain a better understanding of participant perceptions from P9 who strongly disagreed with the survey question: ”...I put constant ray last because although it wasn’t very distracting with this task, I can see how it can get distracting with more complex tasks...” Finally, from our visualization comparison and feedback survey, users overall did not seem to show any preference between one condition over the others.

4.5 Summary

The goal of this Chapter was to understand how could we present shared-gaze visualizations to while preserving user’s sense of control and privacy. From our findings, participants did not express a specific preference for one condition over another. Since no universal preference emerged, offering customizable visualization options would be beneficial. Each condition presented unique pros and cons. For example, participants who preferred an instant view of gaze visualizations were satisfied with the constant ray, while others found this continuous display distracting and preferred the gaze hover for its intuitive nature. Clear communication about the visualization system’s current state is essential for user understanding. Our findings suggest avoiding time-dependent triggers that activate automatically, as these diminish users’ sense of control. Instead, hybrid systems combining hover features with object recognition triggers could provide more flexible and predictable visualizations, giving users greater agency while maintaining collaborative benefits during assembly tasks. Finally, we recommend designing non-occlusive visualizations, such as border highlighting around observed items rather than overlays. This addresses the limitation of gaze hover obscuring object details, an insight we apply in Chapter 6 with the outline visualization. A common theme observed across visualization conditions was the distractive nature of always having a visualization in users’ view. While prior work has consistently implemented this practice, little justification is provided aside from motivation from prior research in remote collaboration. In Chapter 5, we investigate whether self-gaze is necessary for proper visualization of shared-gaze.

CHAPTER 5
EXPLORING SELF-GAZE FOR COLLOCATED TASKS IN AUGMENTED REALITY

5.1 Motivation

Chapter 4 provided us with a preliminary examination of shared-gaze visualizations (SGV) in an assembly task. However, the evaluated methods of visualization came with a set of limitations to task, such as users being distracted by their own visualization. In this Chapter, we explore how self-gaze plays a role in the perception and interaction of SGVs during a dynamic industrial task.

Existing methods of shared-gaze visualization have been beneficial in communicating focus, gaze cues have been implemented bi-directional for collocated applications, meaning collaborators see both their partner's and their own gaze visualization [33, 51, 90]. This approach has shown to be occasionally distracting in that it elicits more physical reactions [22] and overwhelming to users when there is too much visual information displayed [51]. In environments where space for visual content is limited, there is a need to reduce the obstruction of gaze cues while preserving their benefits. Current justifications for bi-directional visualization come from prior work in remote collaborations [90, 107]. However, there are clear apparent differences between collocated and remote collaboration. For instance, remote teams need assistance establishing trust among members due to the lack of nonverbal communication such as body language [126]. These barriers are not prevalent in collocated interactions.

One potential method for improving the distracting nature of gaze visualizations is to make only the other person's gaze visualization visible [33]. In a shared-gaze visualization interaction, visualizing a user's own gaze may be unnecessary and only the collaborator's view may need to be present in a user's field of view. Having users view their own eye gaze direction is redundant and uses valuable space in an already limited virtual environment [176].

Based on our observed limitations of SGVs in Chapter 4, we aim to answer whether self-gaze visualization is necessary in a joint collocated collaborative task:

1. What are the benefits/detriments of visualizing self-gaze in a collocated task?

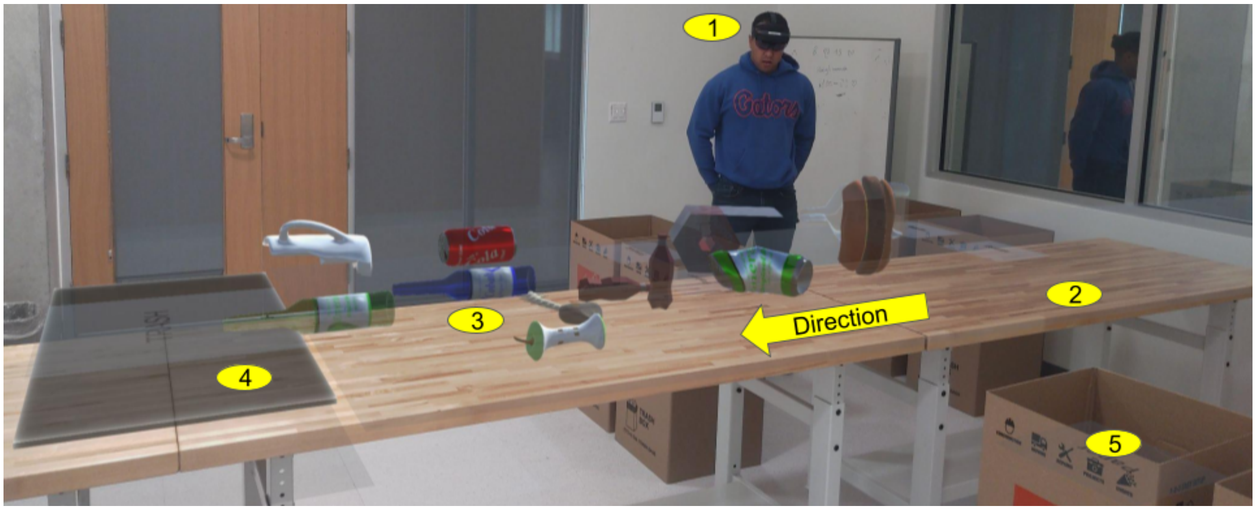


Figure 5-1. Overview of the physical task space with the virtual information laid over. 1) Example participant wearing the Hololens 2 Head Mounted Display. 2) Physical table that divides the participants into their respective spots and in which virtual information is laid over. 3) Virtual recycling debris that participants have to sift through and sort as it moves along the table. The debris moves along the table following the direction pointed out by the arrow. 4) As participants allow debris flow, whatever is left behind goes into the final trash bin. 5) Physical recycling bins in which the virtual debris must be sorted into. Photo courtesy of author.

2. Does the type of visualization affect user's perception of self-gaze?

We analyze two methods for visualizing gaze in augmented reality applications: gaze ray, a red ray extending from the user's view, and gaze hover, which highlights objects the user is looking at. Both methods are implemented in uni- and bi-directional variations.

5.2 Shared-Gaze Visualizations

A common theme in existing solutions is the obstructive nature of gaze visualizations during tasks. For example, gaze rays have been reported as distracting to users [22, 107], and this issue becomes more pronounced in complex tasks [51]. Alternative visualization methods, such as cursors [33] and object highlighting [31, 51], also tend to occlude the user's view.

In response, prior work has focused on designing visualization methods that complement the views of both user's themselves and their partners. For example, different visualization methods have been presented to the user compared to their partner [90], aiming to reduce distraction [198] and mental workload [107]. However, an assumption has been made based on

Figure 5-2. Bi-directional gaze ray. The gaze ray is visualized for both ourselves and our partner. Photo courtesy of author.

Figure 5-3. Uni-directional gaze ray. The gaze ray is only visualized for our partner. Photo courtesy of author.

remote collaboration studies [107], that collocated users need to be made aware of their own visualization for feedback [91]. Aside from one study in which user's gaze was visualized asynchronously [33], collocated studies of shared-gaze visualizations have mostly employed bi-directional visualizations.

Overall, uni- and bi-directional gaze visualizations have not been compared in a collocated setting. Prior work has developed gaze visualizations using design methodologies borrowed from remote applications [107]. However, collocated settings provide different affordances that remote collaboration lacks. For instance, remote collaborators often struggle to determine where their partner is looking due to the constrained views of video cameras [98], making remote drawing annotations necessary [69].

Therefore, in this Chapter, we ask whether it is necessary to visualize self gaze collocated settings. We use a series of user reported qualitative data and automatic data collection methods to understand changes in users' gaze behavior depending on uni- and bi- directional gaze visualizations. Similar to Lee et al. [107], we compare conditions in which participant's own gaze is shared and not.

5.3 Methodology

We conducted a within-subjects user study in which we compared two methods of visualizing gaze through uni- and bi-directional implementations. Our study was approved by our Institutional Review Board (Protocol Number IRB202400883).

5.3.1 Visualizations and Directionality

The study was a 2×2 within-subjects design, varying visualization style (gaze ray vs. gaze hover) and implementation (uni-directional vs. bi-directional), resulting in four conditions. The conditions were uni-directional gaze ray, bi-directional gaze ray, uni-directional gaze hover, and bi-directional gaze hover. In uni-directional conditions, participants saw only their collaborator's visualization. In bi-directional conditions, they saw both their own and their partner's visualizations.

The gaze ray condition presents a virtual red line extending from participants head which

Figure 5-4. Bi-directional gaze hover. The gaze hover is visualized for both ourselves and our partner, highlighting both the paper and the leftover food. Photo courtesy of author.

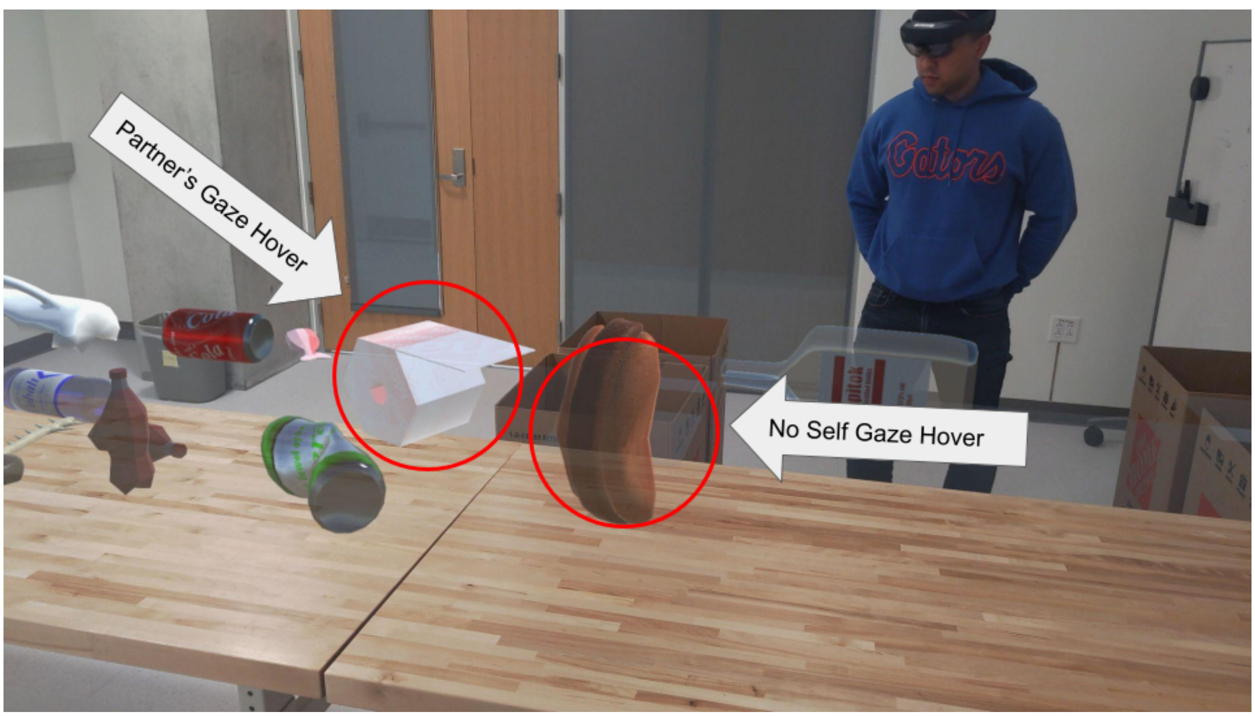


Figure 5-5. Uni-directional gaze hover. The gaze hover is visualized only for our partner, highlighting only the paper. Photo courtesy of author.

Table 5-1. Experimental conditions.

	Ray	Hover
Bi-directional	Condition 1	Condition 3
Uni-directional	Condition 2	Condition 4

points to their current gaze direction which mimics a similar approach used in prior work [33, 51, 132]. The gaze ray visualization is about a yard long and extends a foot out from the users view. An example of the ray visualization is shown in Figure 5-2 and Figure 5-3.

Our inspiration for the gaze hover came from prior implementations of gaze visualization in which objects were annotated using a bright sphere [31] and specific to the context [51]. The current gaze hover implementation provides privacy benefits in reducing what is communicated by only visualizing relevant information, instead of every eye movement [188].

In the gaze hover condition, specific objects are highlighted when users focus on them. If two users look at the same object, the object highlight stays the same. An example of each visualization is shown in Figure 5-4 and Figure 5-5. For the bi-directional gaze condition, the participant across the table is are currently looking at the roll paper and the participant from our point of view is looking at the half-eaten burger. For the uni-directional gaze condition, the participants are looking at the same objects, however, the self-gaze is not highlighted. Therefore, the half-eaten burger remains in its original hue.

5.3.2 Task

The task in this study emulates a sorting process in a recycling plant [30, 191], drawing inspiration from the work of Do et al. [53]. Workers in recycling facilities could benefit from augmented reality (AR) systems that use computer vision to identify dangerous objects, thereby helping to prevent workplace injuries. Furthermore, given the typically loud environment, gaze visualizations could support non-verbal communication between workers. Similar sorting and verification processes are also common in various other industrial applications [48, 187].

This study simulates a scenario in which AR headsets equipped with computer vision tools are used to detect hazardous objects in a recycling plant sorting facility. Workers' communication is supported by shared-gaze visualizations within the AR headsets to aid non-verbal signaling.

Figure 5-6. Dangerous object highlight laid over the sorting task. The dangerous objects—such as broken glass bottles or metal cans—are highlighted among the debris of the rest of the recycling material. Photo courtesy of author.

The task involves users sorting virtual objects as they float down a 3D stream over a physical table. The goal is to sort each object into the appropriate bin based on its designated shape—otherwise, users lose points. Undesirable or dangerous materials must be left untouched (Shown in figure 5-6). These dangerous materials are highlighted with a red hue 80% of the time to emulate current computer vision detection accuracies [164, 192]. A layout of the room is presented in Figure 5-7.

The objects in the scene were set up to move at a speed of 0.3125 meters per second in Unity. The position of the objects was adjusted at 16 millisecond intervals. Each adjustment altered the position by 0.005 meters, thus giving a theoretical speed of 0.3125 m/s. However, the actual observed speed of the objects resulted in being closer to 0.2 m/s in practice. Differences between the theoretical and actual speeds can be attributed to latency within the system used.

Participants are asked to sort four types of recyclable materials: glass, metal, paper, and plastic. An example of the materials is illustrated in Figure 5-1. Additionally, participants must avoid undesirable items (e.g., broken glass and uneaten food). Participants are free to use shared-gaze visualizations and to communicate using any modality they find comfortable.

Before each task, participants are briefed on the nature of the task and the visualization style being used. They are also encouraged to coordinate their actions. In the virtual environment, only one user can interact with an object at a time. As a result, participants must collaborate—if both attempt to grab the same object, it becomes suspended until one user releases it. This constraint promotes the use of shared-gaze visualizations and other available communication modalities.

Scoring is shared between participants, and success is evaluated collectively rather than individually. The virtual environment uses Unity colliders to detect interactions within the task—for example, when one object touches another. Each time an object is correctly sorted into its corresponding bin, a Unity collider logs the event to a file.

5.3.3 Procedure

Participants were recruited from a local university campus through flyers, email recruitment, and word of mouth. Participants could sign up either as a pair or individually. If participants were unable to present as a pair, they were provided with a confederate, supported by a researcher [34]. Out of the 21 participants recruited, only three performed the study with a confederate. Only data from the recruited participants was used for analysis since researchers already had experience with the task and their results would skew the data.

The study began by obtaining informed consent from participants. We then handed each participant a Hololens 2 and performed the device's built-in eye calibration [7]. Once calibration was complete, a researcher would begin our study application. We then performed a pre-study test to ensure the physical and virtual objects were aligned, eye-tracking was functioning, and participants understood the task. The study began once participants could pick up virtual objects using pinch gestures and correctly identify which objects should be recycled.

Participants were given five minutes to sort as many virtual recyclable items as they could. After the five minutes, participants were given a collaboration experience survey. This process

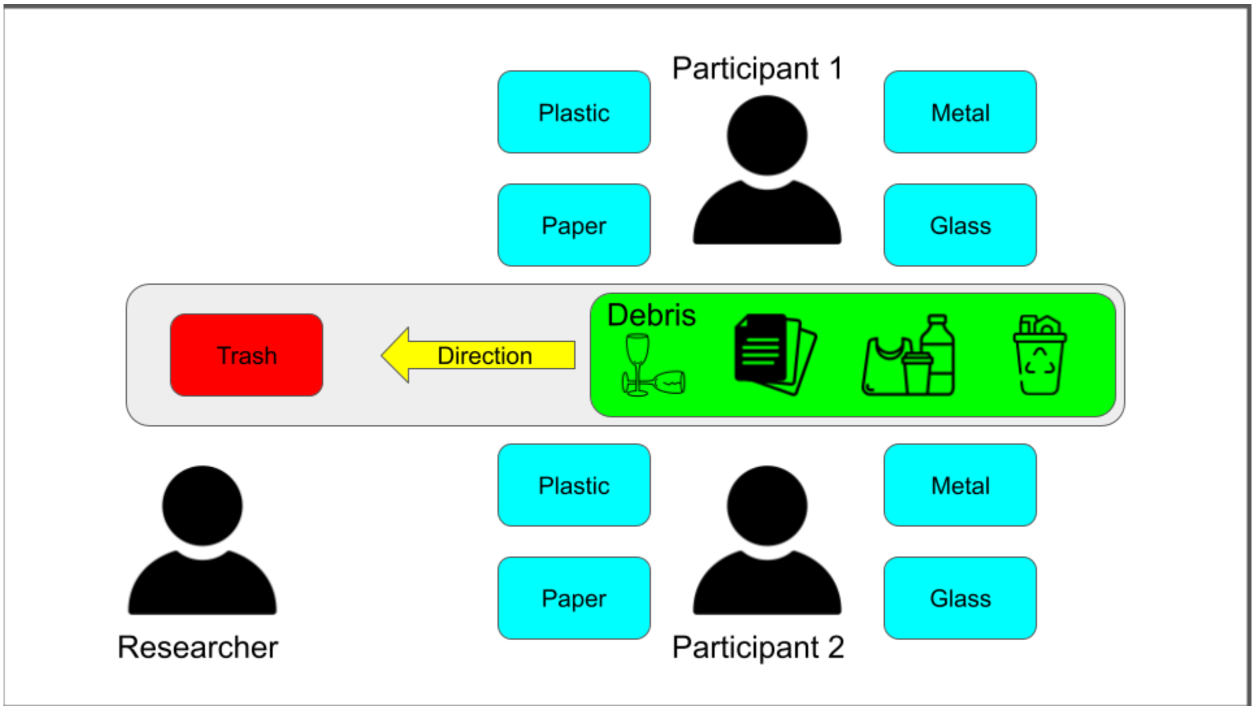


Figure 5-7. Top-down diagram of the task layout which includes bins for recycling material, location of participants within the task, and the direction of debris flow.

was then repeated for each condition. Conditions were counterbalanced across participants using a Balanced-Latin Square. At the end of the four conditions, participants were given the visualization comparison and feedback and demographics surveys. The study took approximately an hour and thirty minutes to complete.

(a) Paper and plastic bins

(b) Metal and glass bins

Figure 5-8. Physical recycling bins overlaid with virtual information. Photos courtesy of author.

5.3.4 Data Collection

For our study, we used both quantitative and qualitative measures. For quantitative measures, we recorded task performance, measured by the number of objects correctly sorted in each condition. We also tracked how often participants interacted with a dangerous object. The Unity application logged each instance of these interactions to a file.

For qualitative measures, we collected a series of collaborative experience, visualization comparison and feedback, and demographic surveys. The application collected user interactions throughout the study which included the number of objects sorted and the number of dangerous objects interacted with. For the collaborative experience survey, we used a modified version of a collaborator workload survey from prior work [51, 90] (Shown in Table 5-2). The survey asks participants about their experiences in the task related to their intentions, focus, attention, reaction, and interaction with the shared-gaze visualization. Participants were asked to rate their agreement with a set of statements on a scale from 1 to 100, in which 1 meant no agreement and 100 meant complete agreement An open-ended response section was included after the agreement statements to allow participants to explain their ratings. The survey statements are shown in Table 5-2. Additionally, we collected a visualization comparison and feedback survey which has participants rank the shared-gaze visualizations and provide a reasoning for their choices. Finally, we collected a demographics survey that collected information on participants' experiences with mixed reality and sorting tasks from current or prior jobs in their personal lives.

5.3.5 Apparatus

As described in Chapter 3, the system was implemented using Unity Engine 2020.3.20f1 running on a Lenovo Yoga Laptop. All command controls were made using the laptop during the study. Two Hololens 2 were used for the main augmented reality platform [176]. The Hololens 2 has built in eye-tracking and the appropriate calibration [7]. For markerless interaction in the physical world, Microsoft Azure Spatial Anchors [77] were used for syncing the environments between headsets [24]. For networking between devices, Photon Engine [44], was used to communicate asynchronously.

Table 5-2. Collaborative Experience survey questions.

Question No.	Survey Element
Intentions	
Q1	"My intentions are accurately represented"
Q2	"My partners intentions are accurately represented to me"
Q3	"I can understand my partners' focus with ease"
Focus	
Q4	"It is better for me to understand my partner's focus"
Q5	"It is better for my partner to understand my focus"
Attention	
Q6	"It is easy to observe my partner's attention"
Q7	"It is easy for my partner to observe my attention"
Reaction	
Q8	"I react to my partner frequently"
Q9	"My partner reacts to me frequently"
Interaction	
Q10	"This form of visualization is effective"
Q11	"This form of visualization is engaging"

5.3.6 Participants

We recruited 21 participants (14 Male, 7 Female) between the ages of 18 and 41 years old (mean 25.43 years, SD = 5.38 years). Most of the participants had some prior experience with a mixed reality system beforehand (14 Yes, 7 No). A majority of participants knew their study partner (14 Yes, 7 No). Additionally, a majority of participants had no experience with sorting tasks (8 Yes, 13 No). Participation in our study was completely voluntary. However, participants were allowed to receive extra credit for applicable courses.

5.4 Results

In this section we present quantitative and qualitative results from our surveys. We compared our data by order of directionality (uni vs bi), visualization style (gaze vs hover), and the interaction effects between the two.

5.4.1 Task Performance

A two-way repeated measures ANOVA was conducted to examine the effect of *Visualization* and *Directionality* on the number of objects sorted and the interaction effects between visualization and directionality. The analysis revealed a significant main effect of Visualization

($F_{1,11} = 5.768, p < 0.05$), but no significant effect of Directionality ($F_{1,11} = 0.164, p = 0.693$) or their interaction $F_{1,11} = 0.051, p = 0.826$.

Table 5-3. Descriptive statistics for the number of objects sorted across conditions.

Visualization	**Directionality**	**Mean**	**SD**	**N**
Ray	Uni	34.7	18.2	12
Ray	Bi	33.1	15.6	12
Hover	Uni	25.4	10.4	12
Hover	Bi	25.1	10.4	12

Table 5-4. ANOVA results for Visualization, Directionality, and their interaction on the number of objects sorted.

Factor	$F_{1,11}$	p-value	η_g^2
Visualization	5.768	**0.035**	0.093
Directionality	0.164	0.693	0.001
Interaction (Vis. $\times$ Dir.)	0.051	0.826	0.0005

Visualization (Ray vs. Hover) There is a statistically significant effect of visualization style on the number of sorted objects ($F_{1,11} = 5.77, p = 0.035, ges = 0.093$). The effect size (generalized eta-squared, ges = 0.093) indicates a small-to-moderate effect. This suggests that participants sorted a different number of objects depending on whether they used the Ray or Hover visualization.

Directionality (Uni vs. Bi-directional) The effect of directionality is not significant. This means there is no strong evidence that sorting performance was affected by whether the visualization was uni- or bi-directional.

Interaction (Visualization × Directionality) The interaction effect is not significant. This suggests that the effect of visualization does not depend on whether the condition was uni- or bi-directional. The effect size is very small, meaning there is little practical impact of this interaction.

The mean number of interactions for dangerous objects per condition are shown in Table 5-5. Differences between conditions were not significant:

A two-way repeated measures ANOVA was conducted to examine the effect of Visualization and Directionality on the number of times users interacted with dangerous objects. The results suggest

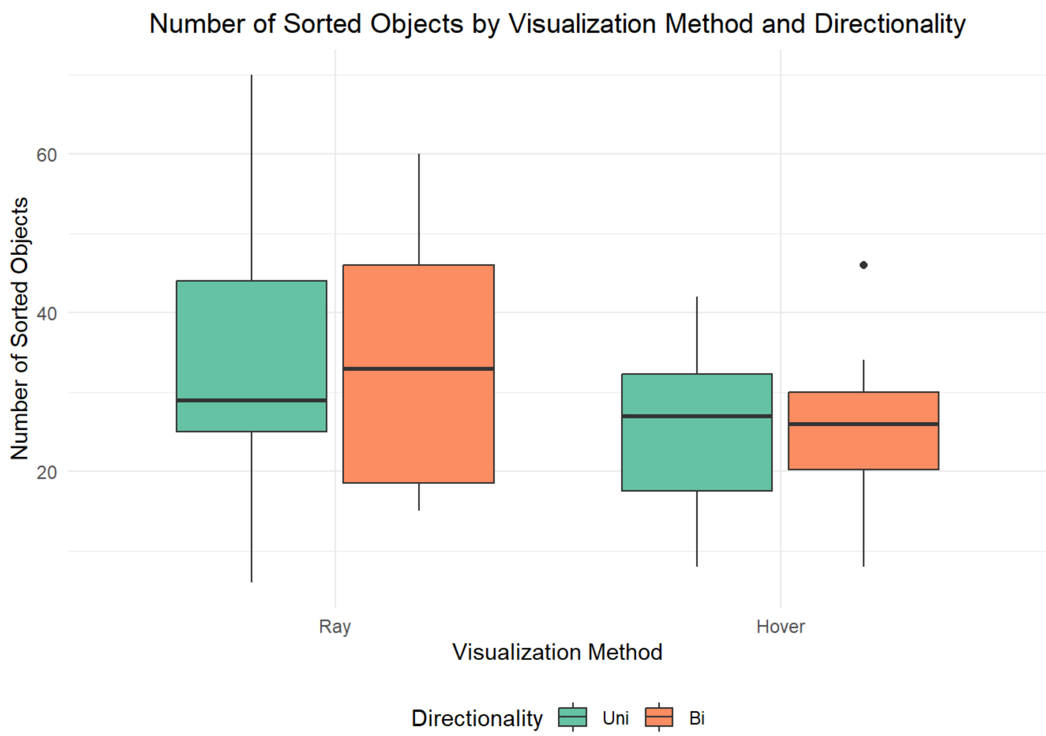


Figure 5-9. Box and whisker plot of number of objects sorted by participants by visualization and directionality.

Table 5-5. Descriptive statistics for interactions with dangerous objects across conditions.

Visualization	Directionality	Mean	SD	N
Ray	Uni	1.08	1.88	12
Ray	Bi	1.08	1.73	12
Hover	Uni	1.33	2.27	12
Hover	Bi	0.75	0.97	12

that neither Visualization ($F_{1,11} = 0.009$) nor Directionality ($F_{1,11} = 0.445$) had a significant effect on the number of interactions with dangerous objects. High standard deviations indicate substantial variability among participants.

5.4.2 Reliability Scale of Collaborative Feedback Survey

To assess the internal consistency of the 11-item collaborative feedback questionnaire (Q1 to Q11), we computed Cronbach's alpha. The scale demonstrated excellent reliability, with a raw Cronbach's alpha of 0.94. The standardized alpha was nearly identical ($\alpha = 0.94$), and Guttman's Lambda 6 further supported the scale's reliability ($\lambda_6 = 0.97$). The average inter-item correlation

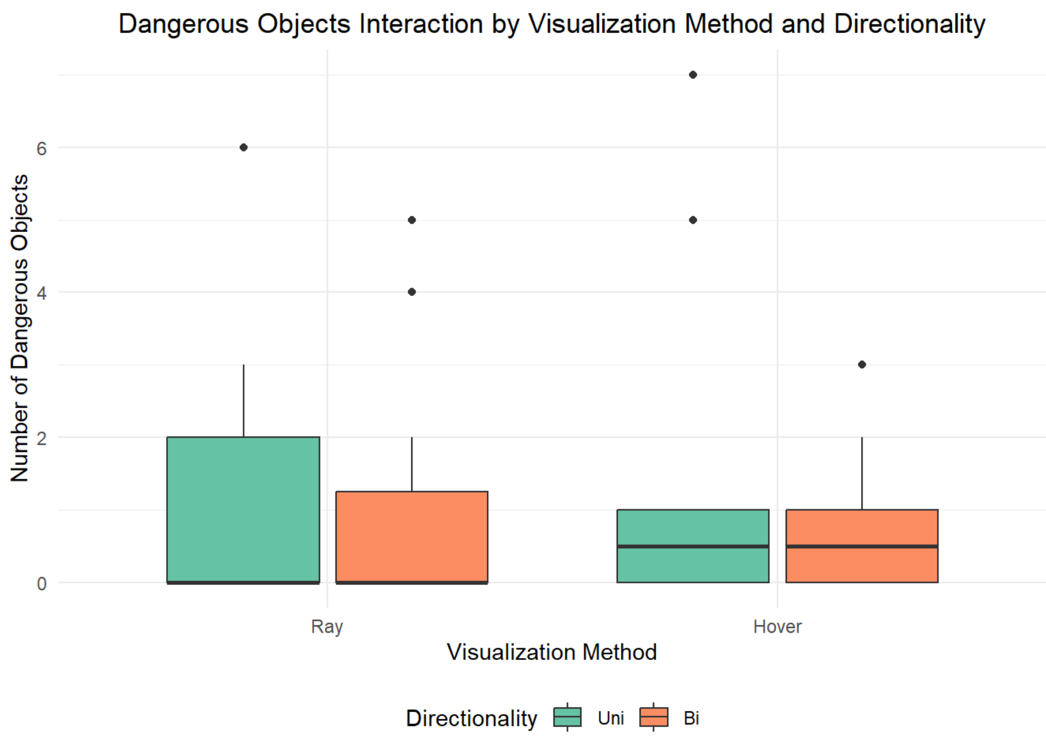


Figure 5-10. Number of dangerous objects users interacted with based on visualization and diretion.

was 0.60, with a median inter-item correlation of 0.55, indicating strong item coherence.

5.4.3 Analysis of Collaborative Experience Survey Responses

The results from the collaborative experience survey did not meet the parametric assumptions required for ANOVA. Therefore, we applied an ArtANOVA test [95] to compare the effects of directionality and visualization style, treating the data as paired within subjects. Significant effects are reported based on p-values. Survey results are illustrated in Figures 5-11 and 5-12 for directionality, and Figures 5-13 and 5-14 for visualization style.

The ArtANOVA analysis examined the effects of Directionality, Visualization, and their interaction across the eleven collaborative experience survey measures (Q1 to Q11), as shown in Table 5-2. The results are summarized as follows:

Visualization (Ray vs. Hover) Visualization showed significant effects in 7 out of 11 measures. The strongest effects were observed in Q2 ”My partners intentions are accurately represented to me” ($F_{1,60} = 12.91, p = 0.001$), Q3 ”I can understand my partners’ focus with ease”

($F_{1,60} = 12.15, p = 0.001$), Q6 ”It is easy to observe my partner’s attention” ($F_{1,60} = 7.57, p = 0.008$), and Q10 ”This form of visualization is effective” ($F_{1,60} = 8.26, p = 0.006$), all of which reached a high level of statistical significance ($p < 0.01$). Additional significant effects ($p < 0.05$) were found in Q1 ”My intentions are accurately represented” ($F_{1,60} = 6.61, p = 0.013$), Q4 ”It is better for me to understand my partner’s focus” ($F_{1,60} = 5.51, p = 0.022$), Q5 ”It is better for my partner to understand my focus” ($F_{1,60} = 4.96, p = 0.030$), and Q7 ”It is easy for my partner to observe my attention” ($F_{1,60} = 6.43, p = 0.014$). In contrast, Q8 ($F_{1,60} = 2.25$), Q9 ($F_{1,60} = 1.26$), and Q11 ($F_{1,60} = 3.40$) did not reach significance. These results suggest that the visualization style had a strong influence on participant responses, particularly in Q2, Q3, Q6, and Q10, where effects were highly significant.

The results indicate that the visualization style (Ray vs. Hover) significantly influenced participants’ perceptions in multiple areas related to mutual awareness and effectiveness. The strongest effects ($p < 0.01$) were found in measures related to understanding a partner’s ATTENTION (Q6) and INTENTION (Q2, Q3) and INTERACTION (Q10). This suggests that Ray provided a clearer representation of a partner’s gaze and attention, improving participants’ ability to interpret their partner’s focus with ease.

Additional significant effects ($p < 0.05$) in Q1, Q4, Q5, and Q7 further reinforce this trend, showing that visualization impacted how well participants felt their own focus was conveyed and how effectively they could interpret their partner’s gaze. However, measures related to broader observational aspects (Q8, Q9, Q11) did not reach significance, indicating that while visualization strongly influenced direct perception and ease of understanding, it may have had less impact on other aspects of the interaction.

Overall, these results highlight the importance of visualization style in facilitating gaze awareness and mutual understanding, particularly in direct measures of focus comprehension.

Directionality did not reach statistical significance in any measure ($p > 0.05$ for all tests).

Interaction (Visualization × Directionality) Interaction effects were non-significant across all

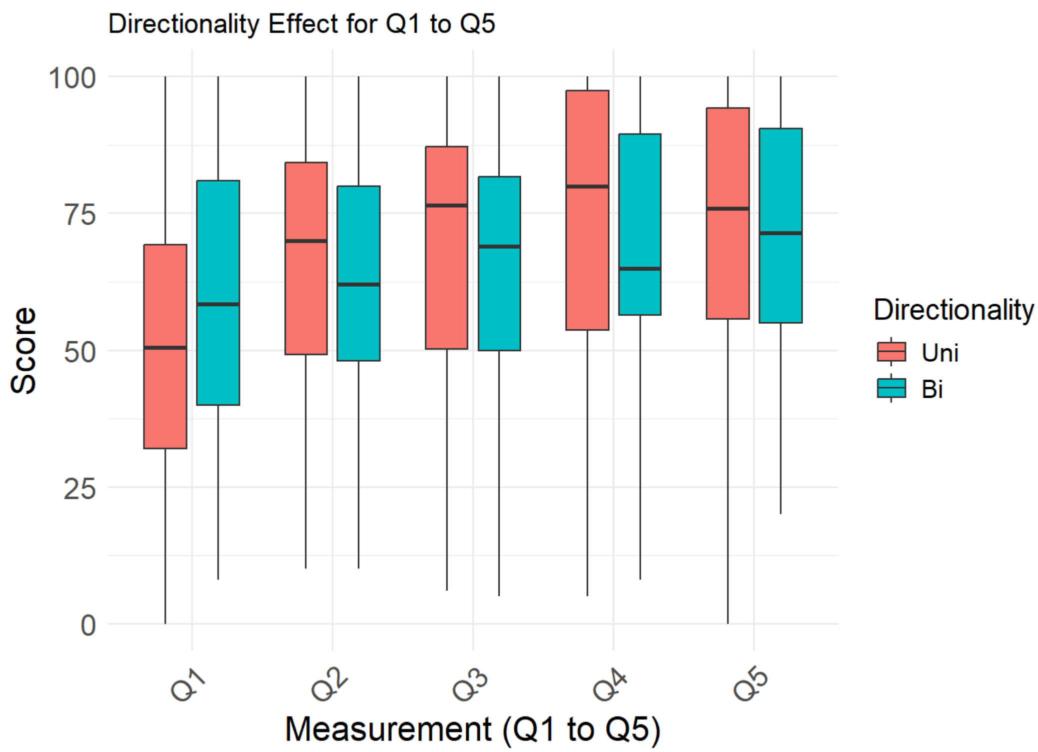


Figure 5-11. Survey responses Q1 to Q5. A rating of 0 meant participants did not agree with the statement at all, while a rating of 100 meant they fully agreed.

measures, with $p > 0.05$ in every case. These findings indicate that the effect of Visualization was independent of Directionality, meaning that the visualization style had a consistent effect across conditions regardless of whether gaze directionality was uni- or bi-directional.

Key takeaways from the analysis are as follows. First, Visualization had a significant effect on many of the collaborative experience survey measures, particularly Q2, Q3, Q6, and Q10 (Table 6-1). Second, Directionality did not significantly impact responses. Finally, no significant interaction effects were observed, meaning that Directionality did not modify the impact of Visualization. These findings suggest that the type of visualization influenced participants' responses, but whether gaze directionality was uni- or bi-directional did not play a major role, with Q1 being the only measure almost reaching significance. Additionally, interaction effects between both directionality and visualization were not significant. Results are summarized in Table 5-6.

Table 5-6. Summary of ArtANOVA Results for the collaborative experience survey. Significance codes are indicated by : $p < 0.01$ '**' and $p < 0.05$ '*'.

Measure	Effect	F	p	Significance
Q1 "My intentions are accurately represented"	Directionality	3.12	0.082	
	Visualization	6.61	**0.013**	*
	Interaction	0.13	0.718	
Q2 "My partners intentions are accurately represented to me"	Directionality	1.00	0.322	
	Visualization	12.91	**0.001**	**
	Interaction	0.10	0.753	
Q3 "I can understand my partners' focus with ease"	Directionality	0.71	0.403	
	Visualization	12.15	**0.001**	**
	Interaction	0.01	0.907	
Q4 "It is better for me to understand my partner's focus"	Directionality	2.42	0.125	
	Visualization	5.51	**0.022**	*
	Interaction	0.04	0.834	
Q5 "It is better for my partner to understand my focus"	Directionality	0.18	0.675	
	Visualization	4.96	**0.030**	*
	Interaction	0.01	0.919	
Q6 "It is easy to observe my partner's attention"	Directionality	0.83	0.367	
	Visualization	7.57	**0.008**	**
	Interaction	0.02	0.882	
Q7 "It is easy for my partner to observe my attention"	Directionality	0.78	0.380	
	Visualization	6.43	**0.014**	*
	Interaction	1.00	0.322	
Q8 "I react to partner frequently"	Directionality	0.96	0.331	
	Visualization	2.25	0.139	
	Interaction	0.58	0.449	
Q9 "My partner reacts to me frequently"	Directionality	1.01	0.319	
	Visualization	1.26	0.266	
	Interaction	3.36	0.072	
Q10 "This form of visualization is effective"	Directionality	0.41	0.524	
	Visualization	8.26	**0.006**	**
	Interaction	0.29	0.590	
Q11 "This form of visualization is engaging"	Directionality	0.18	0.671	
	Visualization	3.40	0.070	
	Interaction	1.37	0.247	

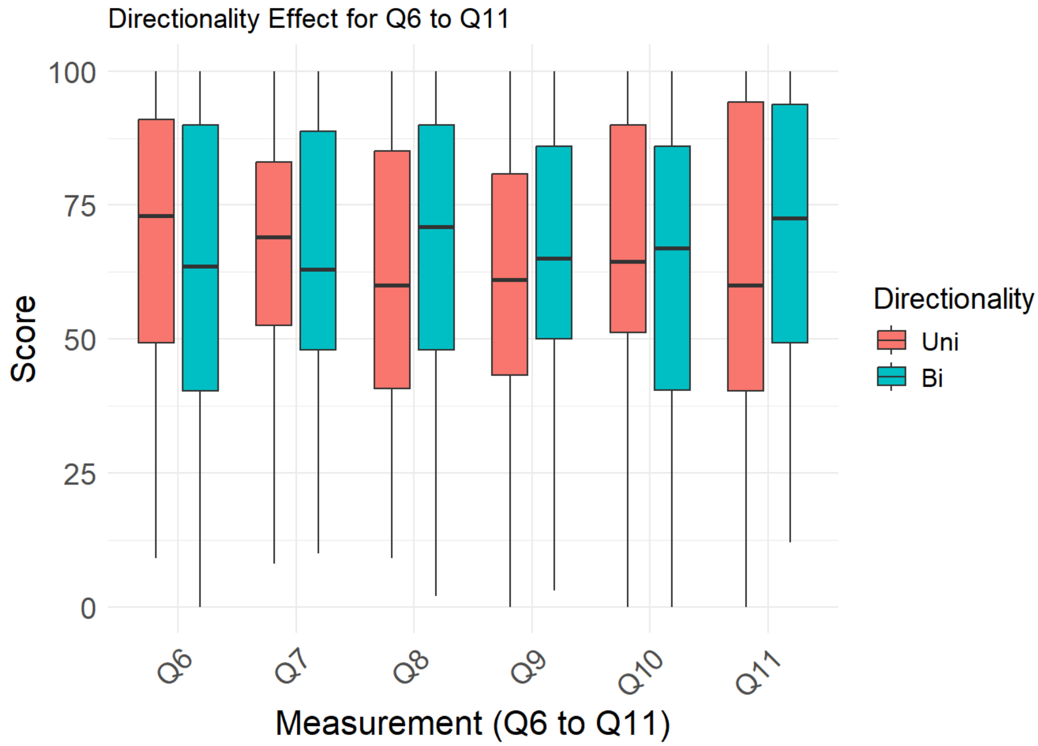


Figure 5-12. Survey responses Q6 to Q11. A rating of 0 meant participants did not agree with the statement at all, while a rating of 100 meant they fully agreed.

5.4.4 Qualitative Feedback

Each collaborative experience survey contained open response section which allowed participants to describe their choices. These responses give us a deeper insight into participant's experiences throughout the collaborative interactions.

Although not significant, results from the collaborative experience survey suggested participants felt bi-directionality more accurately represented their intentions compared to uni-directional. A look into the open responses sheds some light as to participants' perceptions.

Throughout the study, participants used gaze visualizations to signal their intentions to grab specific objects, particularly relying on the uni-directional gaze hover to avoid overlap with their partner. However, the lack of self-view in gaze hover reduced confidence, as P9 commented, "I did not like that it was not highlighted ... made me feel like I was doing nothing at all ..." Participant 2 shared similar sentiments remarking that gaze ray in the bi-directional condition was the:

"Best of the alternatives since it clearly showed my attention and my partner's while

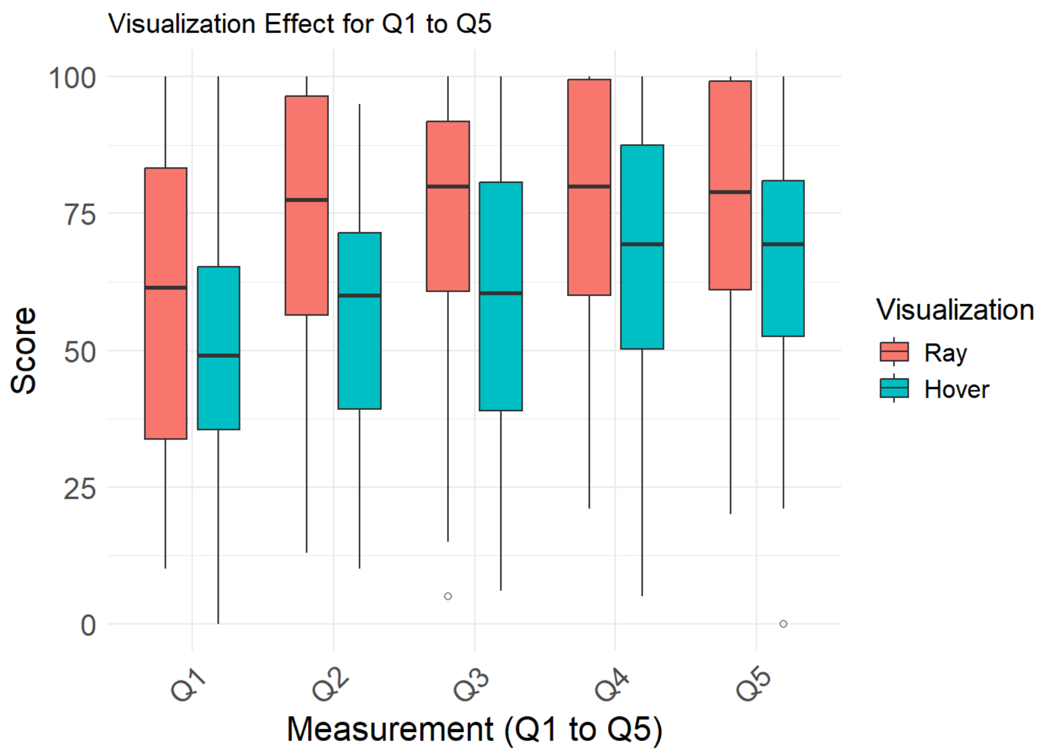


Figure 5-13. Survey responses Q1 to Q5. A rating of 0 meant participants did not agree with the statement at all, while a rating of 100 meant they fully agreed.

> making them distinct to each other. Additionally, the feedback of what I was looking at in addition to the grabbing motion/feedback of the HoloLens which make me more aware of my own attention and purpose."

We saw a similar interest for self-gaze in the hover conditions as well with participant 21 stating:

> "I like this shared-gaze visualization the most. The line visualization cluttered the scene. This highlighting visualization technique was a bit confusing because I wasn't sure if things I was picking up were highlighted or things I was looking at were highlighted. Also I feel that gaze detection is not as accurate as detecting things I'm picking up. Still, this technique allowed me and my collaborator to not need to communicate, we got through all the items quickly and focused on recycling items that were closer to us and the highlights helped us know what doesn't need to be

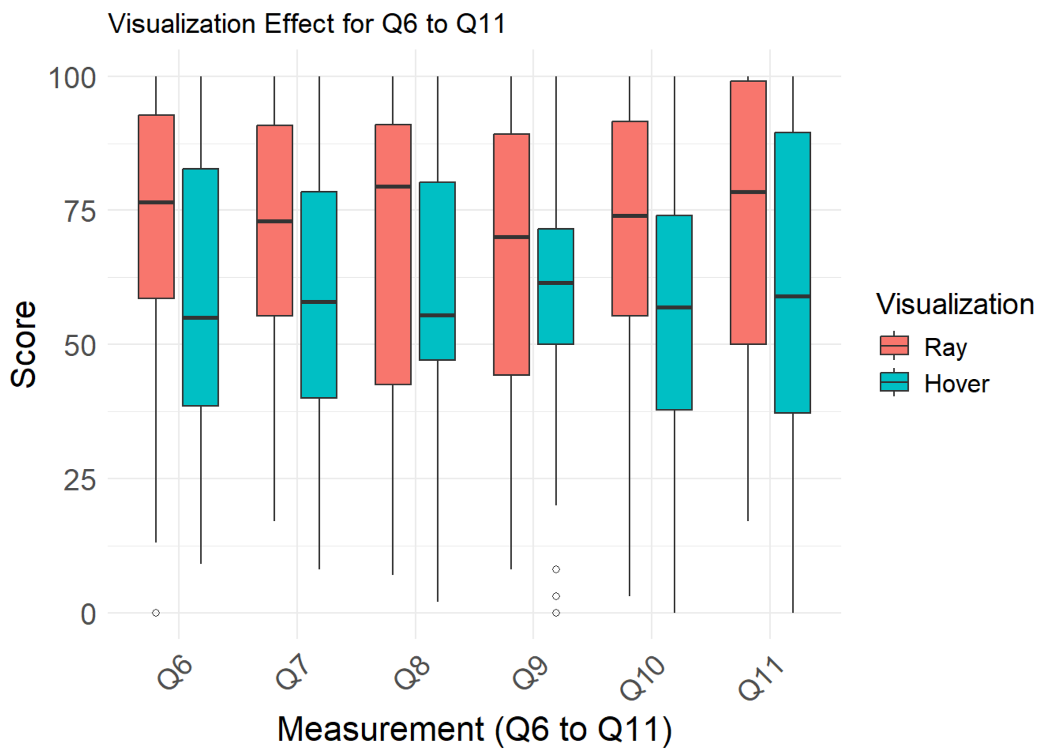


Figure 5-14. Survey responses Q6 to Q11. A rating of 0 meant participants did not agree with the statement at all, while a rating of 100 meant they fully agreed.

picked up because the collaborator is handling it."

Although results indicated that participants favored the bi-directional conditions, we still observed notable contradictions to bi-directionality. For instance, participants found the self-gaze to be unfavorable describing the bi-directional condition to be "Very useful since it lets me see where they're looking at, [however] slightly confusing since i see my gaze too." Participants additionally enjoyed the reduced virtual content in uni-directional conditions, with participant 12 noting the uni-directional gaze ray "...effective at showing where my partner was looking, without the distraction of my own focus." We noticed participants feeling like the self-gaze was distracting with participant 12 also remarking the uni-directional gaze-hover condition "... was very effective at showing where my partner was looking, without the distraction of my own focus."

Regarding visualization preferences, participants consistently rated the ray condition higher than the hover condition across eight different measures (Q1-Q7 and Q10). The ray visualization was perceived as more accurate for representing both the user's own intentions and their partner's intentions. Participants also found that ray visualization made their partner's focus clearer and easier to understand, while simultaneously helping their partner understand their focus. Additionally, the ray condition made it easier for participants to observe their partner's attention and for partners to observe the participants' attention. Overall, participants evaluated the gaze ray as a more effective visualization technique compared to the hover visualization.

A look into open responses highlights participants opinions. Participants found it easier to grasp their partner's focus with gaze ray conditions, especially in the uni-directional case. For example, one participant stated, ”I think this one [uni-directional gaze] is better than the others [conditions] because it lets me see what he is seeing without overloading my view. I don't really need to know what I'm looking at, but what he's looking at helps me (P20).”

The absence of cues associating each gaze hover led to confusion about whose visualization was whose, requiring participants to take extra steps to communicate their actions. For instance, Participant 3 remarked, the gaze hover visualization was ”Very ineffective since I had to communicate using my voice more with my partner.”

5.4.5 Visualization Comparison and Feedback Survey

In the post study questionnaire, we asked participants to rank their preference of visualization type. Based on these results, we ran a Wilcoxon Signed-Rank Test and found no significant difference between preferences of the uni- and bi-directional gaze ray and hover conditions. In regards to understanding participants view on the visual cues, we found that a slight majority of them found them helpful for identifying dangerous objects in context of the shared-gaze visualizations. Participants gave mixed opinions on their perceptions of the visual cues . For instance, participant 13 noted how the cues ”... made the objects more detectable, and therefore avoidable”. However, participant 16 stated ”[I] didn't really notice them.” Overall, participants were more focused on the core task and the shared-gaze visualizations.

5.4.6 Summary of Results

When considering task performance, the type of visualization had a significant effect on the number of objects participants sorted, with participants sorting more objects when using the ray

Table 5-7. Results for the visualization comparison and feedback survey.

Choice	Ranked 1st	Ranked 2nd	Total Responses
Ray	14	7	21
Hover	7	14	21

(a) Survey results for ”Rank the shared-gaze visualization technique.”

Choice	Ranked 1st	Ranked 2nd	Total Responses
Ray	12	9	21
Hover	9	12	21

(b) Survey results for ”Rank the shared-gaze visualization technique with in the context of sorting.”

Response	Count
Yes	12
No	9

(c) Survey responses for ”Were the visual cues helpful in avoiding dangerous items?”

visualization compared to the hover visualization. The type of visualization had a significant effect on measures Q1–Q7 and Q10 from the collaborative experience survey. Overall, these findings highlight the impact of visualization style on gaze awareness and mutual understanding, particularly in the comprehension of focus. Open-ended responses from the collaborative experience survey provided deeper insights into participant interaction.

5.5 Discussion

Self-Gaze in a Collocated Task Results showed no significant difference between measures when comparing them by directionality. Measure Q1 in the collaborative experience survey showed a trend with participants suggesting that their intentions were more accurately represented while using the bi-directional conditions. Participants provided valid reasons for using and opting-out of self-gaze in collaborative interactions. A leading reason for participants preferring self-gaze was otherwise feeling left out and reducing their confidence. This is consistent with prior work in remote work in which participants felt greater presence within the task when their own visualization was visible [79, 107].

Visualization and Directionality Compared to prior work in remote gaze visualization [107], we compare two different methods of self-gaze. While participants were able to sort more virtual objects while using the ray visualization compared to the hover visualization, overall quantitative results suggest that the type of visualization did not affect user perceptions of directionality. Interaction effects between directionality and visualization were not significant.

5.5.1 Showing Ownership of Gaze Visualizations

The confusion associated with gaze hover may stem from participants' unfamiliarity with whose visualization represented whom. The uni-directional conditions aided understanding, as participants knew only their partner's view would be visualized. In the bi-directional conditions, however, participants often needed to take extra steps to clarify their intentions and actions to avoid conflicting with their partner—for instance, reaching for the same object due to mistaken assumptions about ownership of the visual cue. The difference in ease between gaze ray and gaze hover can be attributed to participants' ability to associate the ray with their partner, as it originates from the other person's head and reorients with their movements. When designing a gaze visualization where ownership is not immediately clear, a uni-directional approach may help. Alternatively, adding an external cue that explicitly shows ownership can help reduce confusion. For example, prior implementations have used color to indicate ownership [90]. However, adding visual elements may risk increasing distraction rather than aiding clarity.

5.5.2 On/Off Gaze Visualizations

A compromise to uni- and bi-directional gaze visualization would be turning on self-gaze at necessary points during an interaction. By allowing participants to choose when they want to see would provide them the benefits associated with self-gaze, such as confidence from feedback [107] and reassurance of fair participation as seen from our results, while removing the distractions of constant view of self-gaze. Methods for controlling the current state of gaze visualizations could be implemented through multi-modal interactions, however it is important to consider the importance of each modality to natural human interactions. For instance, voice control could interfere with verbal communication, while gestural control could restrict the user's body movements. If designing automatic methods of visualizing gaze visualizations, it is important to consider the frequency of activation. More clutter in an already dynamic environment can prove to be more distracting than beneficial.

5.6 Summary

The goal of this chapter was to answer the question: How does self-gaze affect user perception of shared-gaze visualizations in augmented reality? In this chapter, we present the findings of a user evaluation of uni- and bi-directional gaze ray and gaze hover during a collaborative industrial task in augmented reality. Our results showed that participants found it more convenient to only show their partner's shared-gaze visualization while completing a dynamic task. However, the lack of self-gaze visualization presents some hurdles when their partner's visualization is visible. For example, participants felt like they were not participating in the task and relied on self-gaze as a feedback cue to reassure themselves of what their partner were seeing. A leading reason for participants preferring self-gaze was otherwise feeling left out and reducing their confidence.

Regarding whether the type of visualization affects user's perception of self-gaze, overall quantitative results suggest that the type of visualization did not affect user perceptions of directionality. Throughout the study, participants employed multi-modal forms for communicating attention, in conjunction with their eye-gaze visualization. Participants were seen using body and hand gestures to confirm actions and vocal communication to clear up any confusions. Furthermore, participants remarked on how the gaze visualizations were seen as an extension of the other person once they became comfortable with them. However, these benefits were lessened when participants found themselves distracted by the visualizations. Particularly with the bi-directional gaze hover condition, where participants had to overcome the confusion of the visualization. In chapter 6, we investigate how an external stimuli (sound) affects users perceptions of visualizations and observe eye-gaze interactions and how the type of simulated experience alters participants non-verbal communication. Through these findings, we provide some design considerations for implementing uni- and bi-directional gaze ray and hover. The two SGVs used in this study, gaze ray and hover, implement different approaches for visualizing gaze, however, they do not encompass the whole spectrum of possible implementations. In Chapter 6, we explore an alternative to ray and hover: the outline visualization.

CHAPTER 6
THE EFFECTS OF SOUND ON THE PERCEPTION OF SHARED-GAZE VISUALIZATIONS IN AN INDUSTRIAL SORTING TASK WITH VISUAL CUES

6.1 Motivation

Based on the design recommendations from Chapters 4 and 5, we evaluate how the outline visualization compares to ray and hover techniques. Our research examines how multi-modal interactions, particularly external stimuli such as sound, affect users' perceptions of visualizations. We also observe eye-gaze interactions and analyze how different types of simulated experiences alter participants' non-verbal communication patterns. Drawing from our findings Chapter 5, we implemented a bi-directional approach specifically designed to prevent participants from feeling disconnected from the task and to preserve their sense of presence and engagement throughout the experience.

Shared-gaze visualizations (SGV) show potential in addressing the social communication challenges of current augmented reality systems. With the advent of eye-tracking in augmented reality headsets, such as the Hololens 2 [176], we can more accurately measure user's attention and provide visualization support [151]. SGV allow collaborators to more accurately predict their intentions than without them [2, 97].

However, limitations arise when attempting to extend them to industrial applications. For instance, sound has been shown to enhance immersion in AR [201, 200], yet most studies on SGV have not explored the impact of sound stimuli on collaborator communication. Previous research has primarily focused on SGV in controlled environments with minimal external factors. Gaze-ray visualizations have been found to improve communication with low mental workload [90], but participants reported feeling more connected when using moving trace visualizations [33]. Gaze-ray also prompted physical reactions, indicating it may have been distracting [22]. Additionally, little investigation has been conducted into how SGV affect users' perceptions of visual cues in context.

Sound has been shown to enhance the sense of presence in virtual reality, with prior work simulating ambient stimuli such as air drafts, vibrations, and even smells [171]. In augmented reality, the use of 3D sound has been found to improve presence in collaborative tasks and assist users in identifying spatial objects [201]. Furthermore, sound plays a critical role in guided augmented reality, making it essential for extending AR systems to real-world industrial applications [195].

To this regard, we aim to answer the following research questions:

- *What are the different effects on social interactions of different types of visualizations and how do they compare to each other?*
- *How does a noisy environment affect dependency on eye-gaze interactions within augmented reality headsets?*
- *How does the presence of SGV affect users' perception of external visual cues?*

We conducted a mixed-effects user study where we evaluate three different shared-gaze visualizations across two different sound (audio noise) conditions while participants performed a virtual industrial task.

6.2 Methodology

We conducted a mixed-effects study using both between-subjects and within-subjects design elements. The experiment included two audio noise (on and off) as a between-subjects factor and three different visualization conditions (ray, hover, and outline) as a within-subjects factor. Participants were exposed to all three visualization types, but they experienced only one consistent sound condition throughout the experiment. For example, participants assigned to the ”sound on” condition experienced all three visualizations with accompanying sound effects, while those assigned to the ”sound off” condition completed all visualization tasks without any audio noise. The study was approved by our Institutional Review Board (Protocol Number ET00041800)

6.2.1 Task

As described in Chapter 3, in order to evaluate the three different gaze and noise conditions through a realistic industrial scenario, the task for the study emulates a sorting recycling plant [30, 191]. Workers from a recycling plant would benefit from an AR system identifying dangerous objects through computer vision aiding in the prevention of work place injuries. Additionally, due

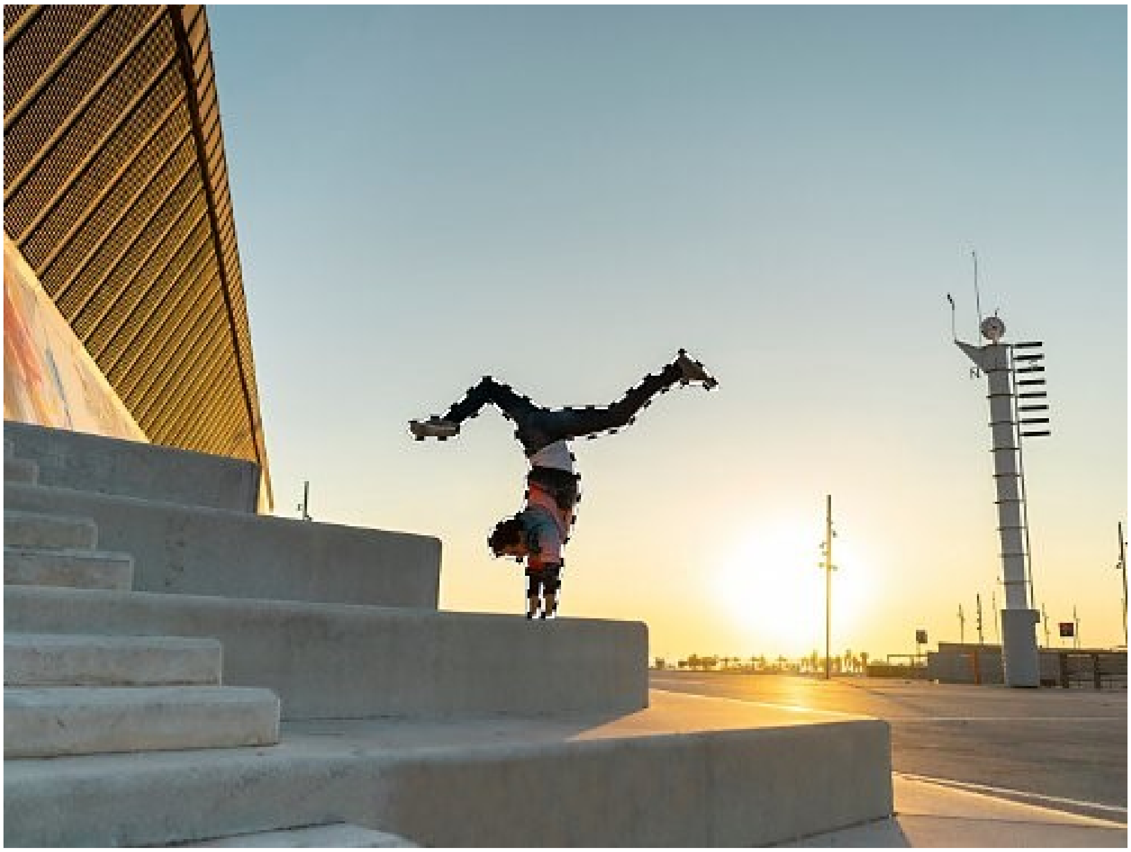


Figure 6-1. Adobe Photoshop magic wand tool used to outline the border of a person. The magic wand tool borders around an area of interest with a black and white border. Source: Westend61. *Acrobat doing handstand on stairs at sunrise [Photograph].* Adobe Stock. Retrieved June 30, 2025, from https://stock.adobe.com/images/acrobat-doing-handstand-on-stairs-at-sunrise/218047735

Figure 6-2. A snippet of a virtual reality task in which participants sorted recycled items to the appropriate bin [53].

to the loud nature of the environment, gaze visualizations between workers could aid in non-verbal communication. Assembly line sorting and verification is prevalent across multiple other industrial applications [48, 103, 187].

Similar to the task described in Chapter 5, participants are asked to sort virtual objects as they float down a 3D stream over a physical table. The goal is to correctly sort each object into the appropriate section based on its designated shape; otherwise, points are deducted. Physical trash bins are used for sorting the recyclable items. Undesirable or dangerous materials must be left untouched. Specifically, dangerous materials—which users are not allowed to interact with—are highlighted in red 80% of the time, simulating real-world computer vision detection accuracy [164, 165, 192].

There are four types of materials to be recycled: glass, metal, paper, and plastic. Additionally, there are undesirable material that should be left alone to be sent directly to a rubbish bin and dangerous objects that users are required to identify. Prior work has implemented a similar task in which users were tasked with sorting recyclable items as they appeared, as shown

Table 6-1. Collaborative Experience survey questions.

Question No.	Survey Element
Intentions	
Q1	”My intentions are accurately represented”
Q2	”My partners intentions are accurately represented to me”
Q3	”I can understand my partners’ focus with ease”
Focus	
Q4	”It is better for me to understand my partner’s focus”
Q5	”It is better for my partner to understand my focus”
Attention	
Q6	”It is easy to observe my partner’s attention”
Q7	”It is easy for my partner to observe my attention”
Reaction	
Q8	”I react to my partner frequently”
Q9	”My partner reacts to me frequently”
Interaction	
Q10	”This form of visualization is effective”
Q11	”This form of visualization is engaging”

in Figure 6-2 [53].

The expectation was that users could work together to prevent each other from being damaged while also focusing on the task. Since the task requires users to give each other attention and the task, the increased intensity of the task is expected to elicit more gaze interactions. The task was created using a Unity 3D engine with Proton Networking engine to allow collaborators to work in the same environment while wearing augmented reality headsets. Users were given an instruction that helps them with identifying the objects to sort out and the objects to leave alone.

6.2.2 Hypotheses

- *H1. Conditions that use the gaze-ray visualization will result in less collaborator eye contact compared to the other visualizations.*
- *H2. The gaze outline condition will result in a greater number of shared objects observed than both the gaze ray and gaze hover conditions.*
- *H3. The sound-on conditions will lead to less eye-gaze interactions (instances) and more eye-contact duration (time).*
- *H4. The gaze-outline conditions will result in less collaborator object collisions (dangerous object interactions).*

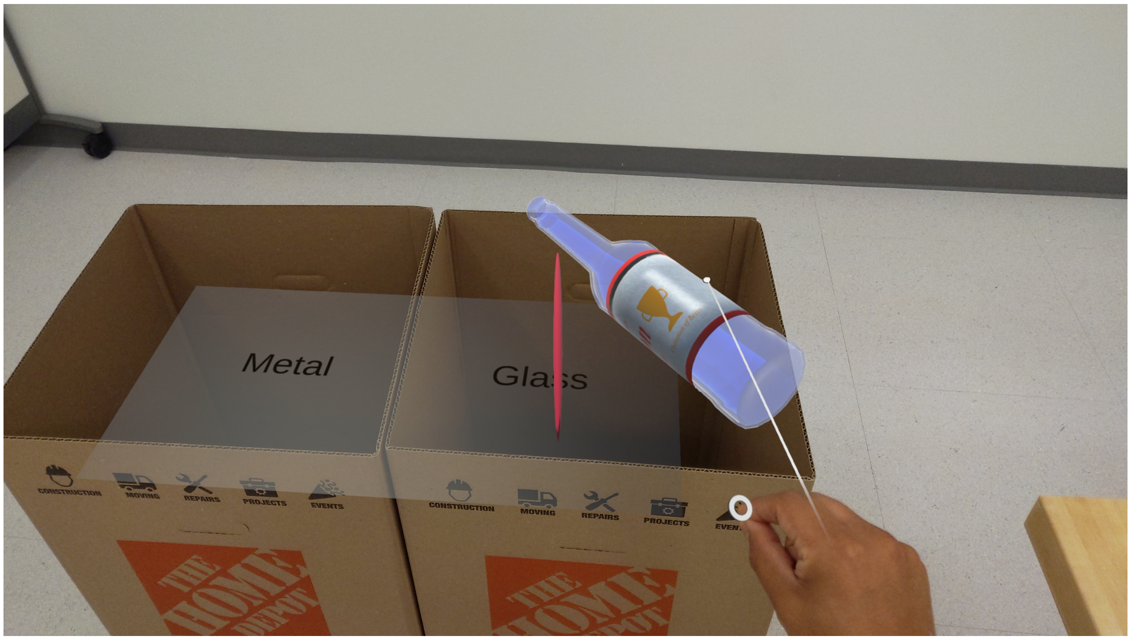


Figure 6-3. Sorting glass bottle into the container. Photo courtesy of author.

- *H5. Participants will find the gaze outline SGV easier to use within in the context of external visual cues compared to the other conditions.*

6.2.3 Visualizations

For the study, participants were exposed to three different type of gaze visualizations and audio stimuli:

- *Gaze visualization*:
  - *Ray*: Same visualization as the one used in the completed works in Chapter 4. The visualization presents a solid red gaze ray extending from the head of the user.
  - *Hover*: Same visualization as the one used in the completed works in Chapter 4 and Chapter 5. The visualization highlights the current object a user is currently looking at and increases the objects hue.
  - *Outline*: A novel gaze-visualization implementation inspired by the Magic Wand tool in Adobe Photoshop [196]. An object's border is emphasized when a user focuses their gaze on it. The border allows the visualization to present a user's current gaze while preserving an object's visual characteristics like surface texture, color, and shape (Shown in Figure 6-5).

6.2.3.1 Gaze-Outline

Based on our findings from Chapter 4 and Chapter 5, gaze-hover only highlighted objects that were specific to context. By having the visualization be specific to the context, a collaborator

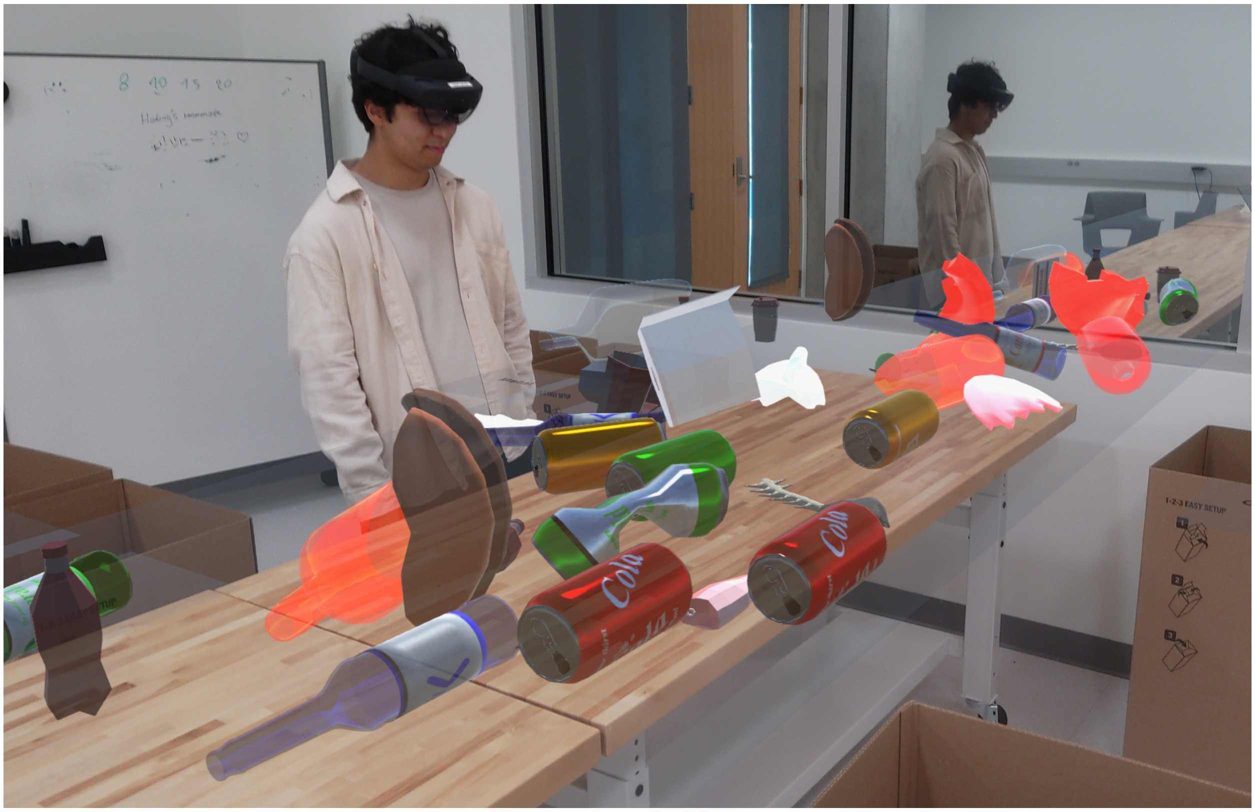


Figure 6-4. This image presents the task space of the study. Users were given four different type of recyclable material to sort from, along with trash, and disposables. The Dangerous objects can be seen mixed in with the general debris and highlighted bright red. Photo courtesy of author.

does not share any extraneous position of where their gaze is currently fixated on. One limitation of gaze-hover was the fact that it could occlude characteristics of an object, such as its original color. So for this study we implement a visualization that borders an object while preserving geometric and surface characteristics of an object.

The inspiration for the gaze-outline design is derived from the magic wand tool in Adobe Photoshop [105, 121, 196]. An example of the magic wand tool can be seen in Figure 6-1. The gaze-outline is implemented similarly, highlighting virtual objects with an outline (Shown in Figure 6-5). The thickness and boldness of the outline was evaluated through pilot testing and remained consistent for the study.

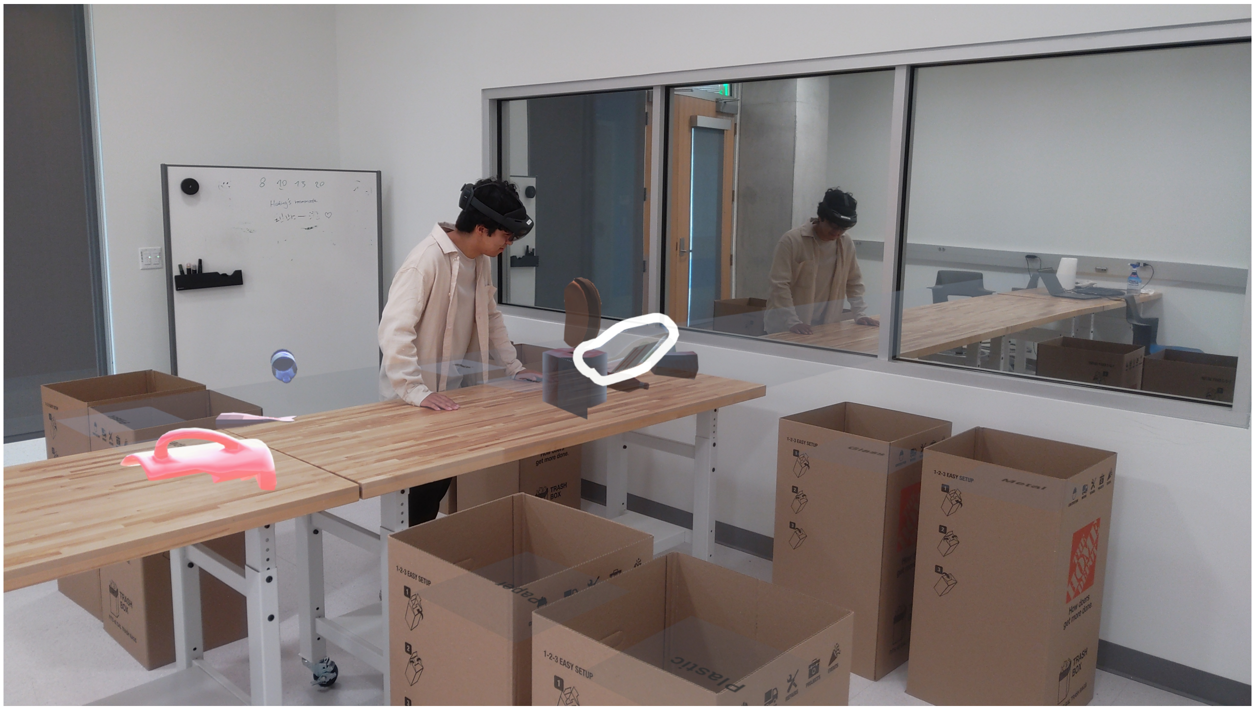


Figure 6-5. Point of view of participant's partner outlining the object they are looking at. The outline creates a 0.5 cm thick border around an object, regardless of the distance. Additionally, it can be observed how the outline preserves the object's geometry and allows user to see the physical details of the object. Photo courtesy of author.

6.2.4 Sound

To enhance the sense of presence in virtual reality, audio noise was implemented using a Unity Audio Source component [102], configured at 0.6 volume and 0.8 pitch to generate white noise [171] (Shown in Figure 3-9). This setup mimics the background noise typically experienced by industrial workers in factories [153]. The volume was set to an identical level of 30% on both HoloLens devices. The sound remained consistent throughout the task, activated at the start and deactivated at the end. The sound level was optimized through pilot testing.

6.2.5 Procedure

A power analysis was conducted based on a medium effect size of 0.25, an alpha level of 0.05, a power of 0.80, and three independent variables. Based on the results of the power analysis, we recruited recruit 20 dyads of participants, totaling to 40 subjects. Participants began the study by first signing an Institutional Review Board (IRB) consent form. Then they placed the Microsoft

Hololens 2 headset and calibrate the eye-tracking. After calibration, participants were taken into a training scene that introduces them to the gaze visualization depending on the current condition. Then participants completed the task. There were three conditions for type of gaze ray and three conditions for speed of the task, which totals to 9 conditions that participants took part in.

After each task, participants filled out a collaborator experience survey which is described in the next section. The collaborator experience is inspired by the NASA-TLX survey and provide us with an understanding of user's workload during the tasks [81, 88]. At the end of the experiment, participants filled out a demographics survey. Participants were recruited at my local institution using Sona-systems [67] and an email listserv. The conditions were counterbalanced using the Latin squares method. Each participant w experience each condition in mixed-effects design. The study took approximately 45-60 minutes.

6.2.6 Measures

During the study, we collected a set of quantitative and qualitative measures to find significant differences between the conditions.

For qualitative measures, we collected a collaborator experience survey used in prior work [51, 90] converted to a 0-100 scale and demographic information. The collaborator experience is inspired by the NASA-TLX survey and provided us with an understanding of user's workload during the tasks [81]. Additionally, we collected an open response survey that asks about participants' experience with each type of visualization.

For quantitative measures, we measured frequency of collaborator eye contact, number of objects directly observed, number of shared objects observed, number of collaborator collisions (grabbing an object at the same time), task completion time, number of dangerous object collisions with each user, and error rate (number of objects not sorted properly after each task). These quantitative measures provide insight into user's gaze interactions depending on the specific conditions.

Unity is capable of adding gaze colliders to objects to collect quantitative data in eye-gaze interactions in real-time. Using colliders, we can count the number of times there are unique

Table 6-2. Direct measures for evaluating shared-gaze visualization (SGV) effectiveness.

Measure	**Description**
Number of eye contact instances	Counts each new instance where participants look at each other's faces simultaneously. Continuous eye contact without gaze shifts counts as one instance. Implemented using an invisible collider on the head in Unity. Assumption: Effective SGV reduces eye contact frequency [123, 144].
Duration of eye contact	Measures the total time participants maintain simultaneous eye contact, regardless of how many separate instances occurred. Assumption: Effective SGV reduces eye contact duration [182, 92].
Number of same objects observed at the same time	Counts new instances when both participants simultaneously look at the same object. Continuous focus on the same object is counted once.
Duration of same objects observed at the same time	Records the total time two participants focus on the same object simultaneously, regardless of how often or when it happens [156, 168].
Comparison between sound and no-sound conditions	All the above measures will be compared between sound and no-sound conditions to evaluate the effect of audio cues on SGV usage.
Number of objects observed	Counts the number of unique objects each user looks at during the study. Revisits to the same object are only counted once.
Qualitative data	Includes a collaborator experience survey adapted from NASA-TLX [81], reported on a 0–100 scale [51, 90], plus free-response feedback to capture participants' subjective experiences with SGV.

collisions of the shared-gaze on an object per user in the environment. Additionally, an invisible object can be added to users in the virtual which allows us to track each time users are making eye-contact. Eye-contact is described as each time a users' eye-gaze collider hits each others' self-referential collider object at the same time. Additionally, eye-contact triggered an internal counter that reports each occurrence. If one user is looking at another but it is not reciprocated, the counter does not go up. All information about gaze interactions were logged onto a log file in real time and saved onto a secured server. Finally, audio and video recordings were collected of participants as they performed the experiments.

6.2.7 Participants

A power analysis was conducted to determine the appropriate sample size, based on a medium effect size of 0.25, an alpha level of 0.05, a power of 0.80, and three independent variables. Based on the results of this analysis, we recruited 20 dyads of participants, totaling 40 subjects. The final participant pool consisted of 40 individuals (24 Male, 16 Female), with ages ranging from 19 to 26 years old (mean = 22.8, std. dev. = 1.192). All participants knew their partners prior to beginning the experiment and had some form of existing social relationship, which helped ensure natural social interactions during the collaborative tasks.

6.3 Results

6.3.1 Collaborative Experience Survey

An Assigned Rank Transform ANOVA was performed to find significant difference between factors in the collaborative experience survey. Then an estimated marginal means was ran for post-hoc analysis.

A two-way ANOVA was conducted to examine the effects of *sound*, *visualization*, and their interaction on responses to *Q2: My partners intentions are accurately represented to me"*. There was no significant main effect of sound ($F_{1,38} = 2.62$), and no significant main effect of visualization ($F_{2,76} = 1.26$). However, there was a significant interaction between sound and visualization ($F_{2,76} = 4.59$, $p = .013$).

Post-hoc pairwise comparisons were conducted using the interaction of *sound* and *visualization* conditions. Most pairwise differences were not statistically significant after adjustment. However, one comparison reached significance: participants in the *sound-on/hover* condition reported significantly different responses compared to those in the *sound-on/outline* condition ($t_{76} = -3.03$, $p = .037$). No other contrasts reached significance ($p > .28$). This suggests participants felt their partner's intentions were more accurately represented them with outline visualization over the hover visualization when sound was on.

A two-way ANOVA on Q11 revealed no significant main effects of *sound* ($F_{1,38} = 2.05$) or *visualization* ($F_{2,76} = 2.36$). However, there was a significant interaction between *sound* and

Table 6-3. ANOVA results for each question and effect. Significant p-values ($p < 0.05$) are bolded and marked with ”*”, and p-values ($p < 0.10$) are bolded and marked with ”.”

Question	Effect	F-value	Df1	Df2	p-value
Q1	sound	1.844	1	38	0.183
	visualization	0.124	2	76	0.883
	sound:visualization	1.812	2	76	0.170
Q2	sound	2.621	1	38	0.114
	visualization	1.265	2	76	0.288
	sound:visualization	4.593	2	76	**0.013 ***
Q3	sound	1.574	1	38	0.217
	visualization	2.740	2	76	**0.071 .**
	sound:visualization	1.560	2	76	0.217
Q4	sound	2.329	1	38	0.135
	visualization	1.785	2	76	0.175
	sound:visualization	2.373	2	76	0.100
Q5	sound	2.648	1	38	0.112
	visualization	1.664	2	76	0.196
	sound:visualization	2.771	2	76	**0.069 .**
Q6	sound	2.669	1	38	0.111
	visualization	0.933	2	76	0.398
	sound:visualization	1.166	2	76	0.317
Q7	sound	2.375	1	38	0.132
	visualization	1.452	2	76	0.240
	sound:visualization	1.736	2	76	0.183
Q8	sound	3.532	1	38	**0.068 .**
	visualization	0.000	2	76	1.000
	sound:visualization	0.304	2	76	0.739
Q9	sound	3.971	1	38	**0.054 .**
	visualization	0.219	2	76	0.804
	sound:visualization	0.018	2	76	0.982
Q10	sound	0.435	1	38	0.514
	visualization	1.735	2	76	0.183
	sound:visualization	1.035	2	76	0.360
Q11	sound	2.047	1	38	0.161
	visualization	2.362	2	76	0.101
	sound:visualization	4.884	2	76	**0.010 ***

visualization ($F_{2,76} = 4.88$, $p = .010$), suggesting that the effect of one factor depends on the level of the other.

Post-hoc comparisons following a significant interaction between *sound* and *visualization* on Q11 revealed no statistically significant pairwise differences ($p > .10$ for all). These results suggest participants found the outline *visualization* to be more engaging than the hover visualization when sound was activated.

A two-way ANOVA revealed no significant main effect of *visualization* style on Q9 ($F_{2,76} = 0.22$), and no significant interaction between sound and visualization, ($F_{2,76} = 0.02$). The main effect of sound was also not significant ($F_{1,38} = 3.97$, $p = .054$).

6.3.2 Visualization Comparison and Feedback Survey

The Friedman rank sum test was performed to examine the differences in rankings across the three conditions (Ray, Hover, and Outline). The result of the Friedman test indicates a significant difference among the conditions ($\chi^2 = 6.65$, $df = 2$, $p - value = 0.03597$). This suggests that the participants' rankings varied significantly across the different conditions.

Following the significant Friedman test, post hoc Wilcoxon signed-rank tests with Bonferroni correction were conducted to identify which pairs of conditions differed significantly. A significant difference was found between the Hover and Outline conditions ($p < 0.05$), while the other comparisons were not significant.

The adjusted p-value for the comparison between Hover and Outline indicates a significant difference ($p < 0.05$) after applying the Bonferroni correction. However, the comparisons between Ray and Hover, and between Ray and Outline, did not show significant differences. Results show participants overall preferred the outline visualization over the hover visualization. A similar questioned was asked to participants about whether the context affected their preference in visualization and statistical analysis should an identical response to the previous response.

6.3.3 Quantitative Measures: Focus Analysis

6.3.3.1 Eye Contact

An Analysis of Variance (ANOVA) on aligned rank transformed data was conducted using a mixed effects model to assess the effects of sound and condition on both the number of eye contact instances and total eye contact time. Type III Wald F tests with Kenward-Roger degrees of freedom evaluated the fixed effects.

For *eye contact instances*, neither the main effects of *sound* ($F_{1,18} = 0.18757$) nor *visualization* ($F_{2,36} = 1.06282$) were statistically significant. The interaction effect was also not significant ($F_{2,36} = 1.85555$).

For *total eye contact time*, the main effects of *sound* ($F_{1,18} = 0.7586$) and *visualization* ($F_{2,36} = 1.5480$) were not significant. The interaction effect, however, was significant ($F_{2,36} = 5.0567$, $p = 0.0116$). Post-hoc comparisons showed significant differences between sound-on, ray and sound-on, outline ($M = 25.8$, $SE = 6.75$, $t = 3.823$, $p = 0.0062$), as well as between sound-on, hover and sound-on, outline ($M = 25.3$, $SE = 6.75$, $t = 3.749$, $p = 0.0076$), suggesting participants spent more time making eye contact in both sound, ray and sound-on, hover, than in sound-on, outline.

6.3.3.2 Shared Focus

ANOVA on aligned rank transformed data assessed the impact of sound and visualization on shared focus instances and total shared focus time.

For *instances*, the effect of sound was not significant ($F_{1,18} = 1.08119$), but visualization had a significant effect ($F_{2,36} = 4.63921$, $p = 0.0161$). The interaction was not significant ($F_{2,36} = 0.96252$). No post-hoc comparisons reached significance after Tukey adjustment. The greatest difference was found between sound-on, hover and sound-on, outline, with the former having a higher score.

For *shared focus time*, no significant effects were found for sound ($F_{1,18} = 1.3706$), visualization ($F2, 36 = 1.3011$), or their interaction ($F_{2,36} = 1.1837$).

6.3.3.3 Glances at Partner

ANOVA evaluated the effects of sound and visualization on both the number of instances and total time participants looked at their partners.

For *instances*, neither sound ($F_{1,18} = 2.84511$), visualization ($F_{2,36} = 0.97039$), nor their interaction ($F_{2,36} = 0.86050$) reached significance.

For *time*, sound approached significance ($F_{1,18} = 4.27994$, $p = 0.0532$), but visualization ($F_{2,36} = 0.73246$) and the interaction effect ($F_{2,36} = 0.76435$) were not significant.

6.3.4 Performance

Two separate analyses of variance (ANOVA) of aligned rank transformed data were performed to examine the effects of sound and visualization on the number of danger objects and the number of sorted objects, using mixed effects models.

For the number of danger objects, the main effects of sound ($F_{1,18} = 0.69522$) and visualization ($F_{2,36} = 0.86297$), and their interaction ($F_{2,36} = 1.14227$) were not statistically significant.

For the number of sorted objects, the main effects of sound ($F_{1,18} = 0.69937$) and visualization ($F_{2,36} = 2.12079$), and their interaction ($F_{2,36} = 0.14619$) were also not statistically significant.

In summary, neither sound nor visualization, nor their interaction, had a statistically significant effect on the number of danger objects or the number of sorted objects.

6.4 Discussion

6.4.1 Summary of Results

Results from the collaborative experience survey suggest that participants felt their partner's intentions were more accurately represented with the outline visualization compared to the hover visualization when sound was on. Participant 4 noted that ”outlines were very visible,” and Participant 35 described them as ”clear for the current task” and helpful for being ”able to differentiate the objects,” which allowed them to understand the visualization ”as the cursor moved around.”

While Participant 3 mentioned they ”never focused on what [their] partner was doing,” they acknowledged that the visualization could be useful ”if me and my partner were fighting over the items.” In contrast, participants described the hover visualization as requiring more effort to interpret, with Participant 12 stating it demanded ”more attention” to see their partner's focus. Overall, participants found the outline visualization to be a more effective representation of their partner's intentions.

Additionally, participants found the outline visualization to be significantly more engaging than the hover visualization in the sound-on condition, per Q11 in the collaborative experience survey. This was also reflected in open-ended responses from the collaborative experience survey. For example, Participant 7 remarked, ”I still think it's a really interesting way to test and experiment with collaboration and teamwork in a fun and engaging way.” In contrast, participants reported difficulty understanding the hover visualization. As Participant 4 noted, ”When objects are close, it is hard to tell which object I grabbed and which my partner grabbed.”

The visualization comparison and feedback survey asked participants to rank their overall visualization preference. Results showed that participants preferred the outline visualization over the hover visualization.

Eye gaze data suggest that participants made significantly more eye contact instances in the sound-off, ray condition than in the sound-on, outline condition. Participants also spent more time making eye contact in both sound-on, ray and sound-on, hover conditions than in sound-on, outline. For instances of shared focus on objects in the environment, the greatest difference was observed between sound-on, hover and sound-on, outline, with the former showing a higher score.

6.4.2 Hypotheses

H1. *Conditions that use the gaze-ray visualization will result in less collaborator eye contact compared to the other visualizations.* **Not supported.** Our findings do not support this hypothesis. Eye contact was observed at similar levels across all conditions, except when sound was on. In the sound-on condition, participants exhibited more eye contact in the ray and hover visualizations compared to the outline visualization.

H2. *The gaze outline condition will result in a greater number of shared objects observed than both the gaze ray and gaze hover conditions.* **Not supported.** Our results suggest that the number of shared objects observed was greater among the hover visualization over the outline visualization during the sound-on condition.

H3. *The sound-on conditions will lead to fewer eye-gaze interactions (instances) and longer eye-contact duration (time).* **Not supported.** Participants exhibited more eye-contact instances in the sound-off ray condition compared to sound-on outline. Additionally, sound alone did not significantly affect eye-contact duration. However, the combination of visualization style and sound condition did influence outcomes: participants made more eye contact in the ray and hover conditions compared to outline when sound was on.

H4. *The gaze-outline conditions will result in less collaborator object collisions (dangerous object interactions).* **Not supported.** An analysis of dangerous objects participants interacted showed no difference between any of the conditions.

H5. *Participants will find the gaze outline SGV easier to use in the context of external visual cues compared to the other conditions.* **Supported.** Results from the collaborative experience survey, eye-gaze analytics, and visualization comparison and feedback survey suggest that the outline visualization effectively communicated intentions and was more engaging than the other visualizations. Overall, participants ranked the outline visualization significantly higher than the others.

6.4.3 Communicating through SGV's

What are the different effects on social interactions of different types of visualizations and how do they compare to each other? Our data shows that sound can have an affect on participants reactions to different visualizations. For example, based on surveys and analytical gaze data, the increase in eye contact for ray, hover over outline in the sound-on conditions suggests that outline was better for communicating over the former.

An increase in eye contact interactions between the ray and hover visualizations over the outline during the sound-on, could be attributed to participants attempting to communicate directly to their partners, bypassing the visualization entirely. Especially, when considering that eye gaze direction is used to regulate interaction [39, 189]. Eye gaze is a fundamental cue used to induce attention from others and regulating interactions [99]. This phenomena is further supported by participants preferences of the outline visualization over the other two. Our results are consistent with prior work, which suggests an increase in eye contact while wearing headsets suggests a lower confidence on the artifacts themselves [144].

6.4.4 Sound and Interaction

How does a noisy environment affect dependency on eye-gaze interactions within augmented reality headsets? Overall, sound influenced the experimental conditions, highlighting the importance of simulating realistic working environments and how external stimuli can alter perceptions of virtual interactions. In our study, participants experienced only one sound condition—either sound-on or sound-off—limiting their exposure and potentially shaping their overall impressions. Sound has been shown to increase immersion [85, 171], and training with sound can improve task performance [200].

6.4.5 Mixed Cues Interaction Space

How does the presence of SGV affect users' perception of external visual cues? Quantitative interaction data from the log files showed there were not significant difference between the type of visualization and user's perception of external visual cues. Our results suggest SGVs can be used in conjunction with other external visual cues. However, more work is needed to find existing limitations.

6.5 Design Recommendations

Based on our findings, we present the following design recommendations for implementing social gaze visualizations in collaborative augmented reality environments:

6.5.1 Environmental Design Considerations

Our study revealed that environmental factors significantly impact how users perceive and interact with gaze visualizations. External stimuli, particularly audio noise, altered participants' utilization and interpretation of different visualization techniques. When designing gaze visualization systems, developers must account for the multi-sensory nature of collaborative environments rather than focusing exclusively on visual elements. The visualization system should also consider how environmental context might change during extended collaborative sessions, potentially adapting visualization properties to maintain optimal visibility and clarity as conditions evolve.

6.5.2 Social Communication Preservation

Our findings demonstrated that visualization techniques significantly impact social communication patterns between collaborators. Different visualization approaches led to measurable differences in eye contact frequency, with the outline visualization resulting in fewer eye contact instances compared to other techniques. Rather than indicating a communication deficit, this reduction suggests that the outline visualization effectively communicated intention information that would otherwise require explicit social signaling through eye contact.

When designing gaze visualizations for collaborative environments, we recommend prioritizing techniques that convey attentional information clearly while minimizing disruption to natural social interaction patterns. The outline visualization in our study demonstrated this balance effectively, providing sufficient information about partners' focus while allowing participants to maintain natural collaborative behaviors.

Designers should evaluate proposed visualization techniques not only for information transmission effectiveness but also for their impact on social dynamics and nonverbal communication patterns. Visualizations that entirely replace rather than supplement natural social cues may unintentionally diminish the richness of collaborative experiences. The optimal approach preserves the fundamental social connection between collaborators while enhancing their spatial and attentional awareness.

6.6 Limitations and Future Work

Our work produced valuable findings; however, we encountered several limitations with the existing methodology. The HoloLens 2 [176], a head-mounted display, posed several constraints that future studies could address. For example, the headset lacked the computing power to simultaneously run the application and record video sessions. Capturing participants' interactions through their point of view (POV) could offer a unique perspective for analyzing eye-gaze behavior.

Additionally, our quantitative eye-gaze measures were based on general regions rather than precise interaction points. For instance, eye contact may have been registered as simply looking toward the general face area due to the large virtual colliders used in Unity. Future work could incorporate more precise and accurate techniques for assessing eye contact in mixed reality environments.

6.7 Summary

The purpose of this chapter was to determine whether sound could alter users' perceptions of shared-gaze visualizations. Building on this idea, we also aimed to explore how different types of visualizations affect social interactions, how a noisy environment influences reliance on eye-gaze interactions during a virtual task, and how the presence of shared-gaze visualizations impacts users' perception of external visual cues.

Motivated by our findings and recommendations in Chapter 4 and Chapter 5, we introduced a new approach to visualizing gaze: outlining the object of interest.

We evaluated three types of shared-gaze visualizations (ray, hover, and outline) across two sound conditions (off and on). We recruited 40 participants for a collaborative user study in which pairs completed a dynamic industrial task together. Our study collected qualitative, quantitative, and descriptive data.

Our results suggest that external stimuli—specifically sound—can influence users' perceptions of shared-gaze visualizations. A decrease in eye-gaze interactions further indicates that participants found the outline visualization less distracting and more engaging than the other two. The visualization comparison and feedback survey responses support this, with participants rating the outline visualization highest on average. Based on our findings, we recommend that future designers of shared-gaze visualizations for mixed reality applications consider the environment in which the tool will be used, particularly the presence of external stimuli such as sound.

CHAPTER 7
ENHANCING COLLABORATOR COMMUNICATION THROUGH SHARED-GAZE VISUALIZATIONS IN AUGMENTED REALITY

My dissertation presented a broad study of shared-gaze visualizations in simulated settings. The overall goal was to determine how can we aid collaborators in industrial tasks through shared-gaze information in augmented reality. In this chapter, we discuss the implications of our findings across all three studies, along with design recommendations and further inquiries for future work.

7.1 Control and Privacy

Eye gaze is an essential component of nonverbal communication and works in unison with other forms, including verbal communication. Eye contact conveys shared attention [99]. For instance, avoiding eye contact while someone is speaking may give the impression of ignoring them [99, 189]. Through nonverbal signaling, eye gaze also influences group decision-making [99, 167]. Moreover, it provides cues of intention and can be used to predict a person's decisions based on their current gaze direction [2].

With an understanding of the importance of natural eye-based communication, we set out to answer the question: How can we present shared-gaze visualizations while preserving users' sense of control and privacy during an assembly task? In this work, we explore the implications of continuous eye-tracking and gaze awareness among collaborators.

7.1.1 Preserving Social Cohesion

Our research across multiple studies highlights the importance of visualization designs that maintain social cohesion in collaborative virtual environments. Chapter 5 revealed that participants expressed strong preferences for having access to self-gaze visualizations, primarily because the absence of such feedback left them ”feeling left out” and ”reduced their confidence.” This finding aligns with previous research in remote work environments where participants reported enhanced presence within tasks when their own visualization was visible [79, 107].

Eye gaze analysis from Chapter 6 provided valuable insights into how different visualization conditions affected social interactions between collaborators. Participants made significantly more eye contact instances in the sound-off, ray condition compared to the sound-on, outline condition. Additionally, participants spent more time making eye contact in both sound-on, ray and sound-on, hover conditions than in the sound-on, outline condition. For instances of shared focus on objects in the environment, we observed the greatest difference between sound-on, hover and sound-on, outline conditions, with hover visualization showing higher scores for shared attention.

Our data further demonstrates that audio communication significantly affects how participants interact with different visualizations. The increased eye contact observed with ray and hover visualizations compared to outline visualization during sound-on conditions suggests that participants may have been attempting to communicate directly with their partners when the visualizations were less effective at conveying intentions. This aligns with established research indicating that eye gaze direction serves as a fundamental mechanism for regulating social interactions [39, 189] and inducing attention from others [99].

This pattern of increased eye contact with certain visualizations may indicate lower confidence in those visualization methods. As participants found the outline visualization more effective (as evidenced by their stated preferences), they relied less on direct eye contact for communication. This finding is consistent with prior work suggesting that increased eye contact while wearing headsets may indicate lower confidence in interface artifacts [144], with participants compensating for less effective visualizations by establishing more direct social connections through eye contact.

7.1.2 Disambiguation of Visualizations

Our research highlights the critical importance of clearly distinguishable shared-gaze visualizations (SGVs) in collaborative virtual environments. Chapter 5 revealed significant differences in how participants interpreted and disambiguated various visualization types. The gaze hover visualization frequently led to confusion, primarily stemming from participants' difficulty in determining which visualization belonged to whom. This ambiguity was notably reduced in uni-directional conditions, where participants knew that only their partner's gaze would be visualized.

In bi-directional conditions, where both participants' gazes were simultaneously visualized, users often needed to implement additional communicative strategies to clarify their intentions and avoid conflicts, such as preventing simultaneous reaches for the same object due to misunderstanding of the visual cue. The gaze ray visualization proved easier for participants to understand compared to the hover visualization. This improved clarity can be attributed to the ray's clear point of origin, which emanated directly from their partner's head and dynamically reoriented with their movements. This provided an intuitive spatial reference that helped participants accurately associate the visualization with their partner.

Chapter 5 and Chapter 6 expanded our understanding of how SGVs interact with other visual elements in virtual environments. Quantitative interaction data from log files indicated no significant differences between visualization types in terms of users' perception of external visual cues. This finding suggests that SGVs can be effectively implemented alongside other visual information without creating perceptual conflicts or overwhelming users' visual processing capabilities. However, the study also highlighted the need for additional research to fully understand the potential limitations of integrating multiple visual feedback mechanisms within collaborative virtual environments.

These findings collectively emphasize that the ability to quickly and accurately disambiguate whose gaze is being represented constitutes a fundamental design consideration for effective shared-gaze visualizations. Visualizations that provide clear ownership cues—whether through spatial relationship to the user (as with rays) or through other distinctive visual attributes—are likely to reduce cognitive load and enhance collaborative efficiency in shared virtual spaces.

7.1.3 Implications

Our findings reveal important connections between gaze visualization design, control, and privacy in collaborative environments. The lack of self-gaze feedback led participants to feel excluded and experience reduced confidence, suggesting diminished situational control. Concurrently, disambiguation features increased users' sense of control over visualizations. The privacy dimension emerged distinctly in our sound condition analysis, where ray and hover visualizations showed increased eye-gaze interactions compared to outline visualization when sound was present. This indicates participants were paying more attention to monitoring each other directly rather than focusing solely on their task. While direct visualizations like ray provided clearer understanding of gaze origin, indirect visualizations like outline better preserved privacy by limiting communication to task-relevant objects only. This tension between awareness and privacy highlights the need for balanced visualization designs that provide sufficient contextual information without encouraging excessive mutual monitoring that might compromise users' sense of autonomy.

7.2 Visualization Preference and Self-Gaze

Motivated by our findings in Chapter 4, we questioned whether it is necessary to visualize self-gaze in a collaborative context. Users commented on the distracting nature of constantly seeing visual representations of their own gaze. Existing justifications for visualizing self-gaze were largely based on remote collaboration studies, which do not align with the needs of shared-gaze visualizations in collocated settings.

With this in mind, we evaluated differences in perception between uni-directional and bi-directional gaze visualizations in Chapter 5. The findings from Chapter 5 offered valuable insights into visualization design. However, user preferences for different visualization types were consistently observed throughout Chapters 4 to 6.

Our research across multiple studies revealed nuanced preferences for different gaze visualization techniques in collaborative virtual environments. In Chapter 4, participants showed no strong preference for a particular visualization condition, with each offering distinct advantages. Those who valued immediate feedback on gaze direction preferred the constant ray visualization, while others found this persistent display distracting and favored the more subtle gaze hover option.

Chapter 5 provided insight into the psychological aspects of visualization preferences. Participants expressed a preference for having access to self-gaze information, citing that without it they felt "left out" and experienced reduced confidence in their interactions. Quantitative analysis from this study revealed that while participants sorted more virtual objects with ray visualization compared to hover visualization. However, the type of visualization did not significantly impact users' perception of directionality.

In Chapter 6, the comparison between outline and hover visualizations in collaborative tasks yielded more definitive preferences. When sound was enabled, participants reported that the outline visualization represented their partner's intentions more accurately than the hover visualization. Participants described the outlines as "very visible," "clear for the current task," and helpful for being "able to differentiate the objects." This clarity allowed them to better understand their partner's focus "as the cursor moved around." Conversely, the hover visualization was characterized as requiring "more attention" to interpret effectively.

Furthermore, participants found the outline visualization significantly more engaging than the hover visualization when audio was present. This enhanced engagement was reflected in participants' comments about the collaborative experience being "interesting" and promoting "teamwork in a fun and engaging way." The hover visualization presented practical challenges, particularly when "objects [were] close," making it "hard to tell which object I grabbed and which my partner grabbed." When asked to rank their overall preferences in the post-study survey, participants showed a clear preference for the outline visualization over the hover visualization.

While no clear preference was observed in Chapter 4, Chapters 5 and 6 offered a deeper understanding of user preferences based on context and visualization type. Overall, users' preferences for visualizing their own gaze depended on the task context and their level of participation.

7.3 External Stimuli

Applied systems do not exist in a void. In order to properly develop collaborative systems for real-world applications, we need to study how external stimuli affect users' perceptions of shared-gaze visualization, specifically sound. Understanding these interactions is crucial as collaborative mixed reality environments are increasingly deployed in complex, multi-sensory real-world settings where various stimuli compete for users' attention.

Our findings emphasize the substantial impact of external stimuli, particularly background audio noise, on user experience and interaction patterns within collaborative virtual environments. Chapter 6 demonstrated that sound significantly influenced participants' responses to different visualization conditions, underscoring the importance of accounting for auditory elements when designing and evaluating virtual collaborative interfaces.

The presence or absence of sound altered participants' perceptions of virtual interactions. This highlights the necessity of simulating realistic working environments that incorporate multiple sensory channels when conducting research on virtual collaboration tools. The interaction between audio noise and visual feedback systems appears to be particularly crucial for understanding how users interpret and respond to shared-gaze visualizations.

It is worth noting that our experimental design exposed participants to only one sound condition (sound-on or sound-off) which may have limited their comparative experience and potentially shaped their overall impressions of the visualization techniques. This methodological constraint should be considered when interpreting preferences and behavioral patterns observed across conditions.

Additionally, these results align with previous research demonstrating that sound integration can significantly enhance immersion in virtual environments [85, 171]. Furthermore, prior studies have shown that training with auditory feedback can improve task performance [200], suggesting that the integration of sound into collaborative virtual spaces may provide benefits beyond just communication facilitation.

Our research contributes to a growing understanding that the effectiveness of visual collaboration tools cannot be evaluated in isolation from other sensory inputs. When designing shared-gaze visualizations for practical applications, developers should consider how these visual elements will function within multi-sensory environments that include ambient sounds, and potentially other sensory feedback mechanisms.

7.4 Design Recommendations

Our results highlight a unique set of constraints that further guide us into the future development of shared-gaze visualizations. In this section, we discuss the implication of these findings into the design of implementations.

7.4.1 Avoiding Occlusion

Based on our findings, we strongly recommend designing gaze visualizations that avoid occluding the objects users are examining. Chapter 4 revealed that visualizations which overlay or obscure target objects can hinder users' ability to perceive details and interact efficiently. To address this issue, we suggest implementing visualization techniques that maintain object visibility while still effectively communicating gaze direction and focus.

A particularly promising approach would be to create visualizations that highlight the edges or borders of objects being observed, rather than overlaying content on the objects themselves. This border-based visualization method would preserve the visual integrity of the target object while simultaneously signaling to collaborators which items are currently receiving attention. Such a technique strikes an optimal balance between communicative clarity and visual accessibility.

The border approach offers several advantages: it maintains full visibility of object details that may be crucial for task completion, reduces visual clutter in the shared environment, and still provides clear indication of attentional focus to facilitate coordination between users. Our results from Chapter 6 further support these recommendations with users strongly preferring the outline visualization over the others. Furthermore, our research suggests that this design consideration is fundamental for creating effective shared-gaze visualizations that enhance rather than impede collaborative work in virtual environments.

7.4.2 User Control of Visualizations

Our research across multiple studies highlights the importance of providing users with appropriate control over gaze visualizations in collaborative virtual environments. We recommend implementing customizable visualization systems that allow users to adapt the display of gaze information according to their needs and preferences during different phases of collaboration.

Chapter 4 revealed that when designing trigger-based gaze visualizations, clear communication of the current visualization state is crucial for user understanding and effective utilization. Traditional time-dependent triggers may lack the flexibility needed in dynamic collaborative environments. Instead, we propose implementing context-sensitive triggers that activate visualizations based on meaningful events, such as when an object is recognized in the user's visual field. This approach creates a more intuitive hybrid visualization system that responds to users' actual attention patterns rather than arbitrary timing thresholds.

Building on these findings, Chapter 5 identified a promising compromise between the uni-directional and bi-directional visualization approaches. Rather than permanently enabling or disabling self-gaze visualization, systems should allow users to selectively activate self-gaze during specific interaction phases when such feedback would be most beneficial. This selective approach preserves the advantages of self-gaze—including increased confidence from visual feedback [107] and reassurance of fair participation as observed in our studies—while eliminating the potential distraction of constant self-gaze visualization.

By empowering users with greater control over when and how gaze visualizations appear, collaborative systems can accommodate different working styles, task requirements, and individual preferences. This flexibility may be particularly valuable in complex collaborative scenarios where attention needs may shift rapidly between focused individual work and coordinated team activities.

7.4.3 Multi-Modal Interactions

Our research findings emphasize the need for careful consideration when implementing multi-modal interaction methods for controlling gaze visualizations in collaborative virtual environments. While multi-modal controls offer flexibility, their design must be thoughtfully balanced against potential interference with natural communication channels.

Chapter 5 highlighted several important design considerations regarding the control mechanisms for gaze visualization states. When implementing voice-based controls, designers must carefully evaluate the potential for interference with verbal communication between collaborators. Voice commands intended to manipulate visualization parameters could be confused with conversational speech, disrupting the natural flow of collaboration. Similarly, gestural control mechanisms, while intuitive in many contexts, risk constraining users' freedom of movement if poorly implemented, potentially limiting their ability to interact naturally within the virtual space.

We suggest that multi-modal control systems for gaze visualizations should be designed with contextual awareness, allowing them to adapt to the current collaborative context and minimize interference with primary communication channels. This might include adjusting activation thresholds based on the current task complexity, the number of collaborators present, or the detected level of verbal communication. By thoughtfully implementing such adaptive controls, systems can provide users with the benefits of gaze visualization while preserving the naturalness of their collaborative interactions.

7.4.4 Ownership of Visualization

Our research underscores the critical importance of establishing clear ownership cues in shared-gaze visualizations to support effective collaboration in virtual environments. Chapter 5 revealed that ambiguity regarding which visualization belongs to which participant can significantly impede collaborative efficiency and increase cognitive load.

When designing gaze visualization systems where ownership is not inherently obvious, we recommend two primary approaches. First, implementing a uni-directional visualization strategy—where only one participant's gaze is visualized at a time, which can eliminate confusion by design. This approach is particularly suitable for scenarios with clearly defined roles, such as instructor-learner interactions or expert-novice collaborations.

Alternatively, for scenarios requiring bi-directional gaze awareness, we recommend incorporating explicit visual cues that clearly indicate ownership of each visualization. Previous implementations have successfully used color coding to differentiate between users' gaze visualizations [90], allowing collaborators to quickly identify whose attention is directed where.

Other potential ownership indicators include unique patterns, shapes, or intensity levels that can be consistently associated with specific participants.

For systems supporting larger groups, scalable ownership indicators become even more critical, potentially requiring hierarchical or role-based visualization schemes that help users quickly distinguish between different collaborators' attention patterns without overwhelming the visual field.

7.4.5 Context-Aware Design

Our research emphasizes the importance of context-aware approaches when designing shared-gaze visualizations for collaborative virtual environments. Chapter 6 demonstrated that external stimuli, particularly audio communication, significantly influence how users perceive and interact with different visualization types. This finding highlights the need for visualization systems that adapt to varying environmental conditions rather than implementing one-size-fits-all solutions.

We recommend developing gaze visualization systems that can dynamically adjust their presentation based on environmental factors. For instance, implementations could automatically transition between different visualization styles depending on detected noise levels in the collaborative environment. When verbal communication is limited or impaired by background noise, more explicit and detailed visualizations might be automatically activated to compensate for reduced audio cues. Conversely, in quiet environments with clear verbal communication channels, subtler visualization approaches might be sufficient and less intrusive.

By designing gaze visualizations that respond intelligently to environmental context while still respecting user preferences, collaborative virtual environments can better support natural and effective interactions across a wider range of usage scenarios and conditions.

7.4.6 Social Effects

Our research reveals that the selection of gaze visualization techniques has profound implications for social dynamics in collaborative virtual environments. Chapter 6 demonstrated that different visualization approaches significantly influence how collaborators engage in fundamental social behaviors, particularly patterns of eye contact and attention sharing.

We recommend that designers carefully consider how visualization choices may affect natural social communication between collaborators. Our findings show that visualization techniques directly impact the frequency and duration of eye contact instances between participants, which serves as a critical channel for social connection and communicative regulation. Specifically, the outline visualization technique resulted in reduced instances of eye contact compared to other visualization methods, suggesting that its clarity and effectiveness reduced participants' need to rely on direct eye contact for coordination.

This reduction in eye contact should not be interpreted as a negative outcome, but rather as evidence that the visualization successfully conveyed intention information that would otherwise require explicit social signaling. The outline visualization appeared to preserve essential task-oriented communication while reducing the cognitive load associated with maintaining social awareness, allowing participants to focus more directly on collaborative tasks.

When designing gaze visualizations for collaborative environments, we recommend prioritizing techniques that effectively communicate attentional information while minimizing disruption to natural social interaction patterns. Visualizations should aim to supplement rather than replace social communication channels, providing information that enhances collaboration without forcing users to abandon established social behaviors. The ideal visualization strikes a balance, offering clear attentional cues when needed while allowing natural social dynamics to flourish during collaborative activities.

Systems might benefit from dynamic visualization approaches that adapt their intrusiveness based on detected communication needs, becoming more prominent when explicit coordination is required and more subtle during periods of fluid social interaction.

7.5 Future Work

My work encompasses a breadth of research questions crucial to understanding the role shared-gaze visualizations play in altering interactions in augmented reality. However, many questions remain which are still vital to further improving design methodologies and the effects of interaction to our social ecosystem.

7.5.1 Multi-Modal Interactions

Our research findings point to rich opportunities for future exploration of multi-modal interaction techniques in conjunction with shared-gaze visualizations (SGVs). Chapter 5 revealed that participants naturally employed multiple communication channels while collaborating in virtual environments, integrating the provided gaze visualizations with spontaneous body language, hand gestures, and verbal communication to enhance coordination and resolve ambiguities.

Participants exhibited an interesting adaptation process, eventually perceiving gaze visualizations as natural extensions of their collaboration partners once they became comfortable with the interface. This integration suggests that well-designed gaze visualizations can become intuitively incorporated into users' mental models of their partners' communicative presence. However, this benefit was significantly diminished when visualizations caused confusion or distraction, particularly in the bi-directional gaze hover condition where participants struggled to disambiguate the source and meaning of visual cues.

Future research should systematically investigate how different modalities can be optimally combined to create coherent communication systems in collaborative virtual environments. Studies might examine how gaze visualizations can be designed to complement rather than compete with gestural and verbal communication channels.

Key research questions include:

- How can gaze visualizations be dynamically adjusted based on detected multi-modal interaction patterns?
- What integration strategies allow gaze information to reinforce rather than duplicate information conveyed through other channels?
- How might different visualization techniques perform in scenarios with varying reliance on verbal versus non-verbal communication?
- Can machine learning approaches be employed to recognize when users are struggling with visualization interpretation and adaptively modify the presentation?

Additionally, future work should explore how these multi-modal systems perform across different collaborative contexts, from structured task-oriented scenarios to more free-form creative collaborations. Understanding how different user populations—including those with varied technical expertise, cultural backgrounds, or cognitive styles—integrate multi-modal cues could inform more inclusive design approaches for collaborative virtual environments.

7.5.2 Extensions to Real-World Applications

Our research has demonstrated the potential benefits of shared-gaze visualizations (SGVs) within controlled experimental settings, but significant opportunities exist for expanding this work into more diverse and naturalistic application contexts. As noted in Chapter 5, our investigation was limited to a singular collaborative task, which cannot fully represent the broad ecosystem of potential applications where SGVs might provide value.

Future research should extend beyond controlled virtual environments to examine how gaze visualization techniques can enhance collaboration in more complex real-world scenarios. A particularly promising direction involves investigating the integration of SGVs with physical objects through augmented reality (AR) interfaces. This approach could bridge the gap between digital visualization techniques and tangible interaction contexts, potentially supporting applications in fields such as:

- Collaborative design and prototyping: How might SGVs facilitate communication between designers working with physical prototypes and digital overlays?
- Industrial training and maintenance: Could gaze visualization help experts guide novice technicians through complex procedures involving physical machinery?
- Educational settings: How might teachers and students benefit from gaze awareness when collaborating on physical learning materials enhanced with digital information?
- Healthcare applications: Could surgical teams or medical training scenarios benefit from awareness of colleagues' visual attention on physical anatomy or medical devices?

These explorations should address the technical challenges of accurately mapping gaze visualizations onto physical objects, particularly in dynamic environments where objects may be manipulated, moved, or altered during collaboration. Research should also consider how the presence of physical objects influences users' interpretation of and response to gaze visualizations compared to purely virtual contexts.

Additionally, longitudinal studies examining the integration of SGVs into established work practices could reveal how these technologies might transform collaborative processes over time. Such research would provide valuable insights for designing SGV systems that genuinely enhance productivity and communication in real-world professional and educational settings.

7.5.3 Visualization Design

Our investigations into shared-gaze visualizations (SGVs) have thus far examined limited design approaches, primarily focusing on gaze ray, hover, and outline techniques. As acknowledged in Chapter 5, these implementations represent only a narrow segment of the potentially vast design space for representing visual attention in collaborative virtual environments. Future research should significantly expand the exploration of visualization techniques to develop a more comprehensive understanding of how design choices influence user perception, cognitive load, and collaborative effectiveness.

We recommend systematic investigation of alternative visualization approaches, including but not limited to:

- Event-based gaze triggers: Visualizations that appear only upon specific attentional events (e.g., extended focus, repeated attention shifts between objects, or attention to critical components) might reduce visual clutter while emphasizing meaningful attentional patterns.
- Heat map visualizations: Representing accumulated attention patterns over time could provide collaborators with awareness of their partners' historical focus patterns in addition to current attention.
- Gradient-based approaches: Implementing subtle visual gradients that intensify with attentional duration might communicate both the target and intensity of attention without binary on/off visualization states.
- Semantic visualization: Developing visualizations that adapt based on the semantic significance of attended objects in the context of current collaborative tasks.

Future studies should evaluate these varied approaches across multiple dimensions, including user preference, task performance, cognitive load, learnability, and impact on natural collaborative behaviors. Research should also investigate how different visualization techniques perform across various task types, from highly structured procedural tasks to more exploratory or creative collaborations.

Additionally, studies should examine how visualization preferences and effectiveness might vary across different user populations, including those with varying levels of technical expertise, different cultural backgrounds, or specific accessibility requirements. The development of customizable or adaptive visualization systems that can accommodate individual differences and task-specific requirements represents a particularly promising direction for future work.

7.5.4 User Intent

Our research has revealed a critical gap between users' intentional communication goals and the automated behavior of current gaze visualization systems. As observed in Chapter 4, participants experienced notable confusion when interacting with the gaze trigger visualization, primarily because the system operated based on a simple focus timer rather than responding to users' actual communicative intentions. This disconnect resulted in visualizations activating and deactivating automatically without regard for whether users genuinely intended to signal their attention to collaborators.

Future research should prioritize developing more sophisticated approaches to inferring and representing user intent in gaze visualization systems. This represents a fundamental shift from treating gaze visualization as merely representing raw attentional data toward conceptualizing it as a communication channel that should accurately reflect users' desires to share information with collaborators. Several promising research directions emerge from this perspective:

- Intent classification algorithms: Investigating how machine learning approaches might distinguish between casual looking, intentional examination, and deliberate communicative gazing based on patterns of eye movement, fixation duration, and contextual factors.
- Hybrid control mechanisms: Exploring systems that combine automatic gaze tracking with subtle user-controlled activation methods, allowing users to modulate the visibility or intensity of their gaze visualization through minimal effort.
- Contextual adaptation: Developing systems that learn from collaborative contexts to predict when gaze information is likely to be communicatively relevant, adjusting visualization parameters accordingly.

- Feedback mechanisms: Investigating how providing users with awareness of their own gaze visualization appearance might enable them to more effectively modulate their looking behaviors to achieve communicative goals.
- Intention signaling: Creating specialized eye movement patterns or gaze gestures that users could employ to explicitly indicate communicative intent, distinguishing these from routine attentional shifts.

This research agenda requires interdisciplinary approaches drawing from eye-tracking technology, human-computer interaction, visual attention research, and communication theory. By bridging the gap between raw attentional data and meaningful communicative intent, future gaze visualization systems could significantly enhance the naturalness and effectiveness of collaboration in virtual environments, reducing user confusion and cognitive load while increasing the communicative value of shared-gaze information.

7.5.5 Devices

Our studies investigating shared-gaze visualizations (SGVs) encountered significant hardware limitations that constrained both the experimental design and participants' experiences. These technical challenges highlight important considerations for future research in this domain and underscore the need to explore alternative hardware platforms for implementing and evaluating gaze-based collaborative systems.

Chapter 5 revealed that the HoloLens 2 augmented reality headsets struggled with computational demands when rendering multiple interactive objects, resulting in increased system latency during prolonged use of the SGV application. This performance degradation potentially affected user experience and may have influenced participants' perceptions of the visualization techniques being evaluated. Additionally, the limited brightness capabilities of the HoloLens 2 displays resulted in semi-transparent object renderings, which could have impacted object visibility and the clarity of gaze visualizations.

These hardware constraints were further confirmed in Chapter 6, where we encountered significant processing limitations that prevented simultaneous application execution and video recording. This restriction eliminated the possibility of capturing participants' point-of-view

(POV) footage, which would have provided valuable data for analyzing eye-gaze behavior and interaction patterns from the users' perspectives.

Future research should prioritize exploring alternative hardware platforms that address these limitations. Specifically, investigations should consider:

- Higher-performance AR/VR systems: Evaluating newer generation headsets with improved computational capabilities that can maintain consistent performance throughout extended collaborative sessions.
- Distributed computing approaches: Exploring architectures that offload rendering and visualization processing to external computing resources while maintaining low-latency interactions.
- Enhanced display technologies: Investigating devices with higher brightness ranges and improved display contrast to ensure clear visualization of virtual objects and gaze indicators.
- Integrated recording capabilities: Prioritizing platforms that support simultaneous application execution and high-quality POV recording to enable more comprehensive analysis of user behaviors and interactions.
- Cross-platform implementations: Developing visualization techniques that can function effectively across different hardware ecosystems, from high-end dedicated headsets to more accessible mobile AR platforms.

These technical advancements would not only improve the reliability and ecological validity of future studies but could also expand the potential application domains for SGVs by addressing practical deployment considerations in real-world collaborative environments.

7.5.6 Eye-tracking

Our research has identified significant opportunities for enhancing the precision and analytical depth of eye-tracking methodologies in collaborative mixed reality studies. As noted in Chapter 6, our current quantitative eye-gaze measurements relied on relatively coarse spatial regions rather than precise interaction points, potentially limiting the granularity of our behavioral analyses.

The technical implementation used in our studies classified eye contact based on gaze directed toward general facial regions, utilizing large virtual colliders in Unity to detect intersections with participants' eye-gaze rays. While this approach provided valuable high-level insights into attentional patterns, it lacked the precision necessary to distinguish between subtle but potentially meaningful variations in gaze behavior, such as direct eye-to-eye contact versus attention to other facial features or peripheral awareness.

Future research should prioritize developing and implementing more refined eye-tracking methodologies for mixed reality environments, including:

- Higher-precision eye-tracking algorithms: Investigating techniques that more accurately pinpoint gaze fixation points with sub-centimeter precision, potentially leveraging advances in eye-tracking hardware and computational approaches.
- Dynamic region of interest (ROI) tracking: Implementing systems that can maintain precise gaze detection regions that adjust to participants' movements and posture changes in real-time.
- Multi-level gaze analysis frameworks: Developing analytical approaches that capture both macro-level attention patterns (e.g., which object is being viewed) and micro-level details (e.g., which specific feature of an object receives focus).
- Temporal pattern analysis: Creating methodologies that not only detect instantaneous gaze locations but also capture meaningful temporal sequences and rhythms in gaze behavior during collaborative interactions.
- Contextual interpretation models: Building systems that interpret gaze data relative to ongoing task states and conversational turns, providing richer insight into the functional role of specific gaze behaviors.

These advancements in eye-tracking methodology would enable more nuanced investigations into how gaze visualizations affect the subtle mechanics of visual communication in collaborative mixed reality. Improved precision could reveal interaction patterns currently obscured by methodological limitations, potentially leading to more effective visualization designs that better support natural collaboration dynamics.

Additionally, future studies could explore multimodal analysis techniques that integrate precise eye-tracking data with other behavioral measures such as speech patterns, gestures, and physiological responses to develop comprehensive models of how visual attention interacts with broader communication processes in collaborative environments.

CHAPTER 8
CONCLUSIONS

The Fourth Industrial Revolution and the rise of smart factories are transforming manufacturing processes worldwide, reimagining the role of human workers in production environments. Despite increasing automation, human expertise remains essential, particularly for complex decision-making, adaptability, and oversight. This dissertation addresses the critical need for technologies that enhance human capabilities within these evolving industrial contexts.

Augmented reality (AR) systems offer promising solutions for supporting industrial collaboration by enabling users to share complex information through three-dimensional visualizations, thereby enhancing understanding, critical thinking, and communication. However, these technologies face significant limitations in industrial settings, including environmental challenges such as noise and the fundamental issue of head-mounted displays creating social barriers by obscuring facial expressions and eye contact between collaborators.

Shared-gaze visualizations (SGVs) represent a potential solution to bridge this social disconnect by enabling collaborators to perceive each other's visual attention. Despite their promise, prior research has insufficiently explored SGVs in authentic contexts, with minimal investigation into their social implications. This gap is particularly significant considering that nonverbal communication, especially eye gaze, constitutes a fundamental communication medium deserving careful consideration and study.

Motivated by these challenges, this dissertation addressed the research question: How can we aid collaborators in industrial tasks through shared-gaze information in augmented reality? To answer this question, I conducted three collocated collaborative user studies evaluating shared-gaze visualizations in diverse contexts based on the following questions:

1. *How can we present shared-gaze visualizations while preserving user's sense of control and privacy over the visualizations during an assembly task?*

2. *How does self-gaze affect user perception of shared-gazed visualizations in augmented reality?*

3. *How does audio noise alter users' perceptions of shared-gaze visualization?*

Our findings from each Chapter are summarized in the following sections:

8.1 Preserving Control and Privacy within Shared-Gaze Visualizations

Chapter 4 aimed to answer how shared-gaze visualizations can be presented while preserving users' sense of control and privacy during an assembly task. A within-subjects study comparing three visualization types (ray, hover, and trigger) revealed no clear user preference, suggesting that offering customizable options would best accommodate diverse needs. Each method had strengths: some participants appreciated the immediacy of the ray, while others preferred the less intrusive hover. Overall, clear system feedback and avoiding automatic, time-based triggers are key to supporting user control. A hybrid approach—combining hover features with object-recognition triggers—may offer a more user-centered, flexible solution for collaborative tasks.

8.2 Users' Perceptions of Self-Gaze

Chapter 5 explored how self-gaze influences user perception of shared-gaze visualizations in augmented reality. Through a user study comparing uni- and bi-directional gaze ray and hover visualizations during a collaborative industrial task, we found that participants generally preferred viewing only their partner's gaze. However, the absence of self-gaze sometimes led to feelings of disconnection and reduced confidence, as participants used self-gaze for reassurance and a sense of participation.

Quantitative results indicated that the type of visualization did not significantly affect perceptions of directionality. Participants often relied on multimodal communication—including gestures and speech—alongside gaze cues. Once familiar, users perceived gaze visualizations as extensions of their partners, though this benefit diminished when visualizations became distracting, particularly with the bi-directional hover.

These findings set the stage for Chapter 6, where we examine how external stimuli, such as sound, further influence user perceptions and nonverbal communication in shared-gaze scenarios.

8.3 External Stimuli and Shared-Gaze Visualizations

Finally, Chapter 6 investigated whether sound influences users' perceptions of shared-gaze visualizations. Expanding on prior work, the study also examined how different visualization types affect social interaction, how noise impacts reliance on eye gaze during virtual tasks, and how shared-gaze visualizations shape users' interpretation of external visual cues.

Informed by earlier findings (Chapters 4 and 5), we introduced a new visualization method: outlining the object of interest. We evaluated three visualization types (ray, hover, outline) under two sound conditions (on, off) in a collaborative AR task with 40 participants.

Results showed that sound does influence perception, and that the outline visualization was perceived as less distracting and more engaging, as reflected by reduced eye-gaze dependency and the highest average participant ratings.

8.4 Summary of Contributions

The studies in my dissertation yielded compelling findings that advance the field by providing:

An identification of key design principles for shared-gaze visualizations that balance collaboration with user autonomy. Our study in Chapter 4 identified both opportunities and limitations in existing shared-gaze visualization approaches. The results demonstrated the need to preserve user control and privacy within collaborative settings.

An understanding of how self-gaze affects user perception of shared-gaze visualizations in augmented reality. The findings from Chapter 5 offer insight into user reactions to the absence of their own gaze visualization during a dynamic task. These results underscore the importance of considering social presence in virtual collaboration.

Evidence that environmental sound significantly influences user perception of shared-gaze visualizations. Our findings from Chapter 6 provide evidence that external stimuli can affect how users engage with shared-gaze visualizations in context. These results highlight the importance of accounting for environmental factors when designing such visualizations.

The implications of the dissertation and design recommendations. In Chapter 7, we synthesized key findings across all studies and discussed their broader implications. Based on these, we proposed a set of design recommendations for shared-gaze visualizations in collaborative contexts. Finally, we outlined several relevant directions for future research.

8.5 Broader Impacts

Gaze interactions in augmented reality are at the forefront of innovative natural computer interfaces. With the development of lightweight, mobile head-mounted displays, the benefits of augmented reality headsets can be actualized. Current augmented reality headsets rely on hand-based interactions for maneuvering augmented information [176]. As mentioned before, this presents a limitation since hands may be occupied during a variety of tasks. Hands-free and eye-gaze based interfaces provide an opportunity for overcoming the limitations of hand-gesture based interfaces, particularly during collaborative industrial tasks, where multiple modes of interaction are occupied and a user's attention is in and of itself a valuable resource. My work in enhancing collaborator communication through shared-gaze visualization in augmented reality extends beyond communicating gaze across multiple parties. Through an understanding of gaze interactions and users' gaze behaviors, we can develop more efficient and predictable gaze-based interfaces.

My work makes contributions to contexts beyond industrial applications, extending findings to other environments with similar characteristics, such as surgical settings, learning environments, and emergency response. For instance, gaze interactions have been used for security surveillance and target identification [58, 59, 132]. Gaze interactions provide a direct understanding of a partner's view and interest, allowing collaborators to signal points of interest. My work contributes to this by expanding on existing knowledge of gaze behaviors and users' interpretation of their representation during an augmented reality task, particularly during tasks in which two actual humans are working together in dynamic scenarios. In surgical applications, using gaze visualizations provides a unique opportunity for highlighting points of interest and annotations [194]. Similar to industrial applications, surgeons' hands may be occupied during a task. My work in visualizing gaze and gaze interactions will provide the groundwork for utilizing gaze tools during surgical applications. The coordination of human-robot collaboration is a crucial aspect for ensuring efficient and safe collaboration [150]. My work further advances our understanding of humans' intentions through gaze interactions, which then ensures reliable robot cooperation. Finally, eye contact is a fundamental human trait that is crucial to human-to-human interaction. By understanding how we utilize gaze for everyday interactions, we can support users through social interactions and scenarios [35, 125]. My work contributes to this by providing methods for visualizing eye-gaze interactions through useful and constructive approaches that aid in understanding social intentions.

APPENDIX A
CODE EXAMPLE: GLOBAL POSITIONING OF SHARED-GAZE VISUALIZATIONS

```
//Attain direction from MRTK2 input (origin, direction)
var direction = CoreServices.InputSystem.EyeGazeProvider.GazeDirection;
var origin = CoreServices.InputSystem.EyeGazeProvider.GazeOrigin;

//Calculate global position with direction and origin, assign rotation value
child.transform.position = direction+origin;
child.transform.rotation = Quaternion.LookRotation(direction);
```

APPENDIX B
QUESTIONNAIRES

Default Question Block

Participant ID:

Task number:

Rating Statement

	Strongly Disagree						Strongly Agree				
	0	10	20	30	40	50	60	70	80	90	100
My intentions are accurately represented											
My partners intentions are accurately represented to me											
I can understand my partners' focus with ease											
It is better for me to understand my partner's focus											
It is better for my partner to understand my focus											
It is easy to observe my partner's attention											
It is easy for my partner to observe											

Strongly Disagree Strongly Agree

0 10 20 30 40 50 60 70 80 90 100

my attention

I react to partner frequently

My partner reacts to me frequently

This form of visualization is effective

This form of visualization is engaging

What are your overall opinions on the shared-gaze visualization technique?

What are your overall opinions on the shared-gaze visualization technique within the current context?

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Default Question Block

Participant ID:

Rank the shared-gaze visualization technique:

Constant Ray

Gaze Hover

Gaze Outline

Explain your reasoning for the choices made above.

Rank the shared-gaze visualization technique with in the context of sorting:

Constant Ray

Gaze Hover

Gaze Outline

Explain your reasoning for the choices made above.

Were the visual cues helpful in avoiding dangerous items?

- Yes
- No

Explain your reasoning for the choices made above.

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Default Question Block

Enter Participant ID

Gender

- Male
- Female
- Non-binary / third gender
- Prefer not to say

Age

Please select one of two options

	Yes	No
Do you have 20/20 vision or corrected vision with contact lenses?	○	○
Do you have any experience with virtual reality simulations?	○	○

Do you know your partner?

- Yes
- No

Do you have experience with sorting tasks from prior work?

- ○ Yes
- ○ No

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APPENDIX C
STATISTICAL ANALYSIS: EVALUATION OF SHARED-GAZE VISUALIZATIONS FOR VIRTUAL ASSEMBLY TASKS

```
## ── Attaching core tidyverse packages ──────────────────────── tidyverse 2.0.0 ──
## ✓ dplyr     1.1.4     ✓ readr     2.1.4
## ✓ forcats   1.0.0     ✓ stringr   1.5.1
## ✓ lubridate 1.9.3     ✓ tibble    3.2.1
## ✓ purrr     1.0.2     ✓ tidyr     1.3.0
## ── Conflicts ────────────────────────────────────────── tidyverse_conflicts() ──
## ✗ dplyr::filter() masks stats::filter()
## ✗ dplyr::lag()    masks stats::lag()
## ℹ Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to becom
e errors
##
## Attaching package: 'gridExtra'
##
##
## The following object is masked from 'package:dplyr':
##
##     combine
##
##
##
## Attaching package: 'rstatix'
##
##
## The following objects are masked from 'package:effectsize':
##
##     cohens_d, eta_squared
##
##
## The following object is masked from 'package:stats':
##
##     filter
```

```
##       part            cond         rank
##  Min.   : 1.0   Min.   :1   Min.   :1
##  1st Qu.: 3.0   1st Qu.:1   1st Qu.:1
##  Median : 5.5   Median :2   Median :2
##  Mean   : 5.5   Mean   :2   Mean   :2
##  3rd Qu.: 8.0   3rd Qu.:3   3rd Qu.:3
##  Max.   :10.0   Max.   :3   Max.   :3
```

```
## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties

## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties

## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties
```

```
## [1] "Done..."
```

Friedman

```
##
##  Friedman rank sum test
##
## data:  pcon$Q3_1, pcon$Q0 and pcon$Q1
## Friedman chi-squared = 0.56, df = 2, p-value = 0.7558
```

```
## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties

## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties

## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties
```

```
##
##  Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data:  pcon$Q3_1 and pcon$Q0
##
##   1 2
## 2 1 -
## 3 1 1
##
## P value adjustment method: bonferroni
```

```
##
##  Friedman rank sum test
##
## data:  pcon$Q3_2, pcon$Q0 and pcon$Q1
## Friedman chi-squared = 3.3793, df = 2, p-value = 0.1846
```

```
## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties

## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties

## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties
```

```
##
##  Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data:  pcon$Q3_2 and pcon$Q0
##
##   1    2
## 2 0.62 -
## 3 1.00 1.00
##
## P value adjustment method: bonferroni
```

```
##
##  Friedman rank sum test
##
## data:  pcon$Q3_3, pcon$Q0 and pcon$Q1
## Friedman chi-squared = 1.2258, df = 2, p-value = 0.5418
```

```
## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties

## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties

## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties
```

```
##
##  Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data:  pcon$Q3_3 and pcon$Q0
##
##   1    2
## 2 1.00 -
## 3 0.77 1.00
##
## P value adjustment method: bonferroni
```

```
##
##  Friedman rank sum test
##
## data:  pcon$Q3_4, pcon$Q0 and pcon$Q1
## Friedman chi-squared = 0.25, df = 2, p-value = 0.8825
```

```
## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties

## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties

## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties
```

```
##
##  Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data:  pcon$Q3_4 and pcon$Q0
##
##   1    2
## 2 1.00 -
## 3 1.00 0.48
##
## P value adjustment method: bonferroni
```

```
##
##  Friedman rank sum test
##
## data:  pcon$Q3_5, pcon$Q0 and pcon$Q1
## Friedman chi-squared = 0.9697, df = 2, p-value = 0.6158
```

```
## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties

## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties

## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties
```

```
##
##  Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data:  pcon$Q3_5 and pcon$Q0
##
##   1    2
## 2 1.00 -
## 3 0.49 0.41
##
## P value adjustment method: bonferroni
```

```
##
##  Friedman rank sum test
##
## data:  pcon$Q3_6, pcon$Q0 and pcon$Q1
## Friedman chi-squared = 3.25, df = 2, p-value = 0.1969
```

```
## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties

## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties

## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties
```

```
##
##  Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data:  pcon$Q3_6 and pcon$Q0
##
##   1    2
## 2 1.00 -
## 3 0.45 0.56
##
## P value adjustment method: bonferroni
```

```
##
##  Friedman rank sum test
##
## data:  pcon$Q3_7, pcon$Q0 and pcon$Q1
## Friedman chi-squared = 2.6897, df = 2, p-value = 0.2606
```

```
## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties

## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties

## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties
```

```
##
##  Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data:  pcon$Q3_7 and pcon$Q0
##
##   1    2
## 2 1.00 -
## 3 0.14 0.88
##
## P value adjustment method: bonferroni
```

```
##
##  Friedman rank sum test
##
## data:  pcon$Q3_8, pcon$Q0 and pcon$Q1
## Friedman chi-squared = 3, df = 2, p-value = 0.2231
```

```
## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties

## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties

## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties
```

```
##
##  Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data:  pcon$Q3_8 and pcon$Q0
##
##   1    2
## 2 0.27 -
## 3 0.56 1.00
##
## P value adjustment method: bonferroni
```

```
##
##  Friedman rank sum test
##
## data:  pcon$Q3_9, pcon$Q0 and pcon$Q1
## Friedman chi-squared = 0.63636, df = 2, p-value = 0.7275
```

```
## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties

## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties

## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties
```

```
##
##  Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data:  pcon$Q3_9 and pcon$Q0
##
##   1    2
## 2 1.00 -
## 3 0.94 1.00
##
## P value adjustment method: bonferroni
```

```
##
##  Friedman rank sum test
##
## data:  pcon$Q3_10, pcon$Q0 and pcon$Q1
## Friedman chi-squared = 1.6667, df = 2, p-value = 0.4346
```

```
## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties

## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties

## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties
```

```
##
##  Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data:  pcon$Q3_10 and pcon$Q0
##
##   1 2
## 2 1 -
## 3 1 1
##
## P value adjustment method: bonferroni
```

```
##
##  Friedman rank sum test
##
## data:  pcon$Q3_11, pcon$Q0 and pcon$Q1
## Friedman chi-squared = 1, df = 2, p-value = 0.6065
```

```
## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties

## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties

## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties
```

```
##
##  Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data:  pcon$Q3_11 and pcon$Q0
##
##   1    2
## 2 1.00 -
## 3 1.00 0.82
##
## P value adjustment method: bonferroni
```

Post Study Survey

```
## [1] "Friedman test on pstudy:\n"
```

```
##
##  Friedman rank sum test
##
## data:  pstudy$rank, pstudy$cond and pstudy$part
## Friedman chi-squared = 0.8, df = 2, p-value = 0.6703
```

```
## [1] "Pairwise Wilcox test:\n"
```

```
## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties

## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties

## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties
```

```
##
##  Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data:  pstudy$rank and pstudy$cond
##
##   1    2
## 2 1.00 -
## 3 1.00 0.95
##
## P value adjustment method: bonferroni
```

Note that the `echo = FALSE` parameter was added to the code chunk to prevent printing of the R code that generated the plot.

APPENDIX D
STATISTICAL ANALYSIS: EXPLORING SELF-GAZE FOR COLLOCATED TASKS IN AUGMENTED REALITY

sgv_analysis

2024-10-22

R Markdown

```
## [1] "Demographics Summary..."
```

```
##
## Female   Male
##      7     14
```

```
##
##  No Yes
##   7  14
```

```
##
##  No Yes
##   4  17
```

```
##
##  No Yes
##   7  14
```

```
##
##  No Yes
##  13   8
```

```
##        Q1          Q2                  Q3           Q4_1
##  Min.   : 1   Length:21          Min.   :18.00   Length:21
##  1st Qu.: 6   Class :character   1st Qu.:23.00   Class :character
##  Median :11   Mode  :character   Median :24.00   Mode  :character
##  Mean   :11                      Mean   :25.43
##  3rd Qu.:16                      3rd Qu.:28.00
##  Max.   :21                      Max.   :41.00
##      Q4_2                Q5                 Q6
##  Length:21          Length:21          Length:21
##  Class :character   Class :character   Class :character
##  Mode  :character   Mode  :character   Mode  :character
##
##
##
```

```
## [1] 5.381184
```

```
## [1] "PostStudy Summary..."
```

```
##
##  Wilcoxon signed rank test with continuity correction
##
## data:  data_post$Q2_1 and data_post$Q2_2
## V = 77, p-value = 0.1316
## alternative hypothesis: true location shift is not equal to 0
```

```
##
##  No Yes
##   9  12
```

```
##
##  Wilcoxon signed rank test with continuity correction
##
## data:  data_post$Q4_1 and data_post$Q4_2
## V = 99, p-value = 0.5255
## alternative hypothesis: true location shift is not equal to 0
```

```
##        Q1             Q2_1            Q2_2            Q3
##  Min.   : 1.00   Min.   :1.000   Min.   :1.000   Length:21
##  1st Qu.: 6.00   1st Qu.:1.000   1st Qu.:1.000   Class :character
##  Median :11.00   Median :1.000   Median :2.000   Mode  :character
##  Mean   :10.95   Mean   :1.333   Mean   :1.667
##  3rd Qu.:16.00   3rd Qu.:2.000   3rd Qu.:2.000
##  Max.   :21.00   Max.   :2.000   Max.   :2.000
##       Q4_1            Q4_2            Q5                 Q7
##  Min.   :1.000   Min.   :1.000   Length:21          Length:21
##  1st Qu.:1.000   1st Qu.:1.000   Class :character   Class :character
##  Median :1.000   Median :2.000   Mode  :character   Mode  :character
##  Mean   :1.429   Mean   :1.571
##  3rd Qu.:2.000   3rd Qu.:2.000
##  Max.   :2.000   Max.   :2.000
##       Q8
##  Length:21
##  Class :character
##  Mode  :character
##
##
##
```

```
##        Q1           Q2            Q3_1             Q3_2             Q3_3      
##  Min.   : 1   Min.   :1.00   Min.   :  0.00   Min.   : 10.00   Min.   :  5.00  
##  1st Qu.: 6   1st Qu.:1.75   1st Qu.: 34.25   1st Qu.: 49.00   1st Qu.: 50.00  
##  Median :11   Median :2.50   Median : 54.00   Median : 65.00   Median : 70.00  
##  Mean   :11   Mean   :2.50   Mean   : 55.10   Mean   : 64.29   Mean   : 65.85  
##  3rd Qu.:16   3rd Qu.:3.25   3rd Qu.: 77.25   3rd Qu.: 82.00   3rd Qu.: 84.25  
##  Max.   :21   Max.   :4.00   Max.   :100.00   Max.   :100.00   Max.   :100.00  
##       Q3_4             Q3_5             Q3_6             Q3_7       
##  Min.   :  5.00   Min.   :  0.00   Min.   :  0.00   Min.   :  8.00  
##  1st Qu.: 55.25   1st Qu.: 54.75   1st Qu.: 46.00   1st Qu.: 50.00  
##  Median : 75.00   Median : 73.00   Median : 69.50   Median : 64.50  
##  Mean   : 70.73   Mean   : 70.69   Mean   : 65.07   Mean   : 64.81  
##  3rd Qu.: 92.00   3rd Qu.: 92.25   3rd Qu.: 90.25   3rd Qu.: 85.00  
##  Max.   :100.00   Max.   :100.00   Max.   :100.00   Max.   :100.00  
##       Q3_8             Q3_9           Q3_10            Q3_11       
##  Min.   :  2.00   Min.   :  0.0   Min.   :  0.00   Min.   :  0.00  
##  1st Qu.: 44.75   1st Qu.: 47.5   1st Qu.: 43.75   1st Qu.: 45.25  
##  Median : 67.50   Median : 63.5   Median : 66.00   Median : 66.00  
##  Mean   : 64.83   Mean   : 62.4   Mean   : 62.88   Mean   : 65.98  
##  3rd Qu.: 90.00   3rd Qu.: 83.0   3rd Qu.: 89.25   3rd Qu.: 94.25  
##  Max.   :100.00   Max.   :100.0   Max.   :100.00   Max.   :100.00  
##       Q4                 Q5           
##  Length:84          Length:84          
##  Class :character   Class :character  
##  Mode  :character   Mode  :character  
##                                       
##                                       
## 
```

Actual Data Analysis Under here vvvvvvv

```
## 
##     Uni Bi
##   1   0 21
##   2  21  0
##   3   0 21
##   4  21  0
```

```
## 
##     Ray Hover
##   1  21     0
##   2  21     0
##   3   0    21
##   4   0    21
```

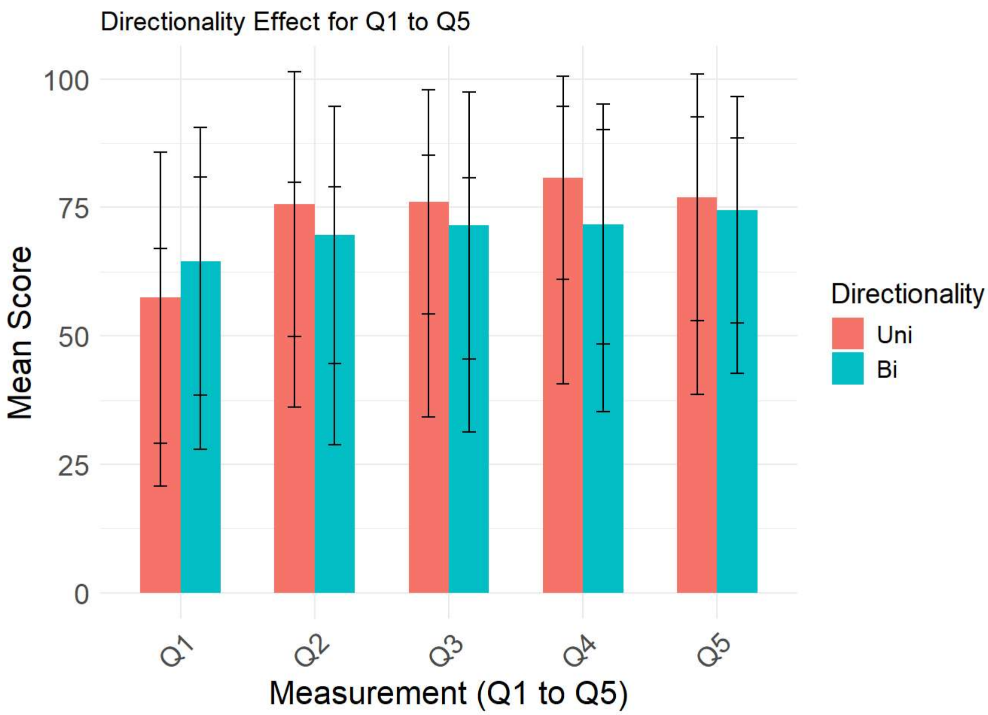
```
##  raw_alpha std.alpha   G6(smc) average_r      S/N         ase     mean       sd
##  0.9422153 0.9422834 0.9681483 0.5974534 16.32603 0.009475338 64.78355 20.85411
##   median_r
##  0.5516092
```

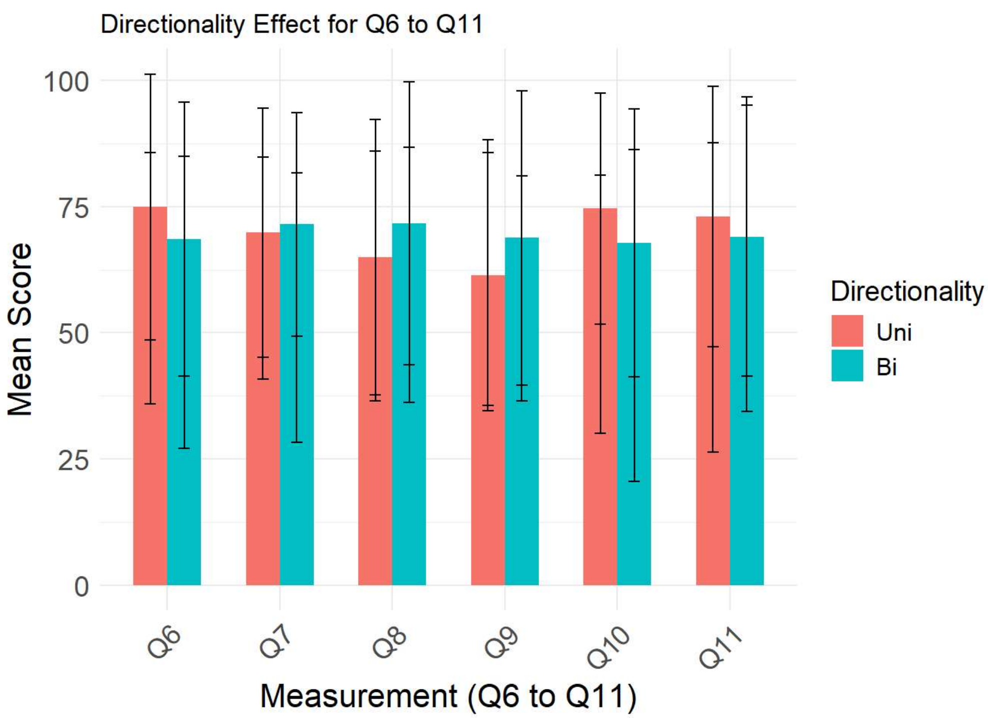
```
##
## Analyzing Q3_1
## Analysis of Variance of Aligned Rank Transformed Data
##
## Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)
## Model: Mixed Effects (lmer)
## Response: art(score)
##
##                                    F Df Df.res   Pr(>F)
## 1 Directionality               3.11866  1     60 0.082488 .
## 2 Visualization                6.61080  1     60 0.012633 *
## 3 Directionality:Visualization 0.13185  1     60 0.717795
## ---
## Signif. codes:   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Analyzing Q3_2
## Analysis of Variance of Aligned Rank Transformed Data
##
## Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)
## Model: Mixed Effects (lmer)
## Response: art(score)
##
##                                      F Df Df.res     Pr(>F)
## 1 Directionality                0.996873  1     60 0.32207808
## 2 Visualization                12.906085  1     60 0.00066157 ***
## 3 Directionality:Visualization  0.099662  1     60 0.75333063
## ---
## Signif. codes:   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Analyzing Q3_3
## Analysis of Variance of Aligned Rank Transformed Data
##
## Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)
## Model: Mixed Effects (lmer)
## Response: art(score)
##
##                                      F Df Df.res     Pr(>F)
## 1 Directionality                0.709923  1     60 0.40281543
## 2 Visualization                12.145776  1     60 0.00092585 ***
## 3 Directionality:Visualization  0.013684  1     60 0.90726681
## ---
## Signif. codes:   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Analyzing Q3_4
## Analysis of Variance of Aligned Rank Transformed Data
##
## Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)
## Model: Mixed Effects (lmer)
## Response: art(score)
##
##                                     F Df Df.res   Pr(>F)
## 1 Directionality               2.419333  1     60 0.125105
```

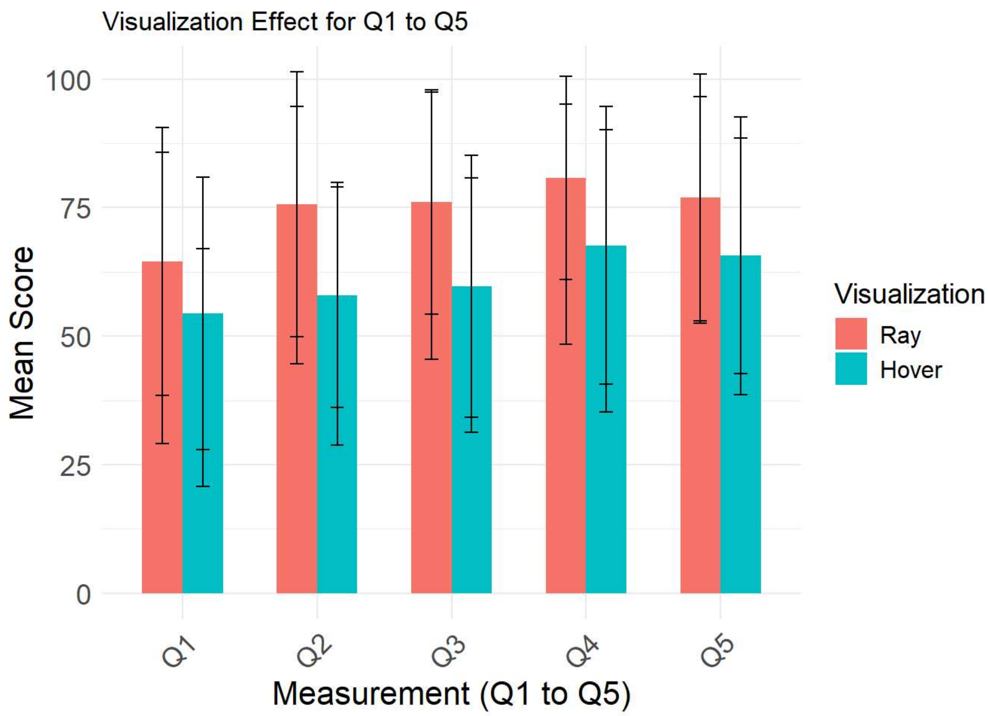
```
## 2 Visualization                5.510951  1     60 0.022214 *
## 3 Directionality:Visualization 0.044254  1     60 0.834095
## ---
## Signif. codes:   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Analyzing Q3_5
## Analysis of Variance of Aligned Rank Transformed Data
##
## Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)
## Model: Mixed Effects (lmer)
## Response: art(score)
##
##                                       F Df Df.res   Pr(>F)
## 1 Directionality               0.177388  1     60 0.675132
## 2 Visualization                4.959996  1     60 0.029704 *
## 3 Directionality:Visualization 0.010306  1     60 0.919477
## ---
## Signif. codes:   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Analyzing Q3_6
## Analysis of Variance of Aligned Rank Transformed Data
##
## Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)
## Model: Mixed Effects (lmer)
## Response: art(score)
##
##                                       F Df Df.res   Pr(>F)
## 1 Directionality               0.825179  1     60 0.367305
## 2 Visualization                7.567632  1     60 0.007845 **
## 3 Directionality:Visualization 0.022276  1     60 0.881855
## ---
## Signif. codes:   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Analyzing Q3_7
## Analysis of Variance of Aligned Rank Transformed Data
##
## Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)
## Model: Mixed Effects (lmer)
## Response: art(score)
##
##                                      F Df Df.res   Pr(>F)
## 1 Directionality               0.78143  1     60 0.380233
## 2 Visualization                6.42943  1     60 0.013847 *
## 3 Directionality:Visualization 0.99862  1     60 0.321659
## ---
## Signif. codes:   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Analyzing Q3_8
## Analysis of Variance of Aligned Rank Transformed Data
##
## Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)
## Model: Mixed Effects (lmer)
```

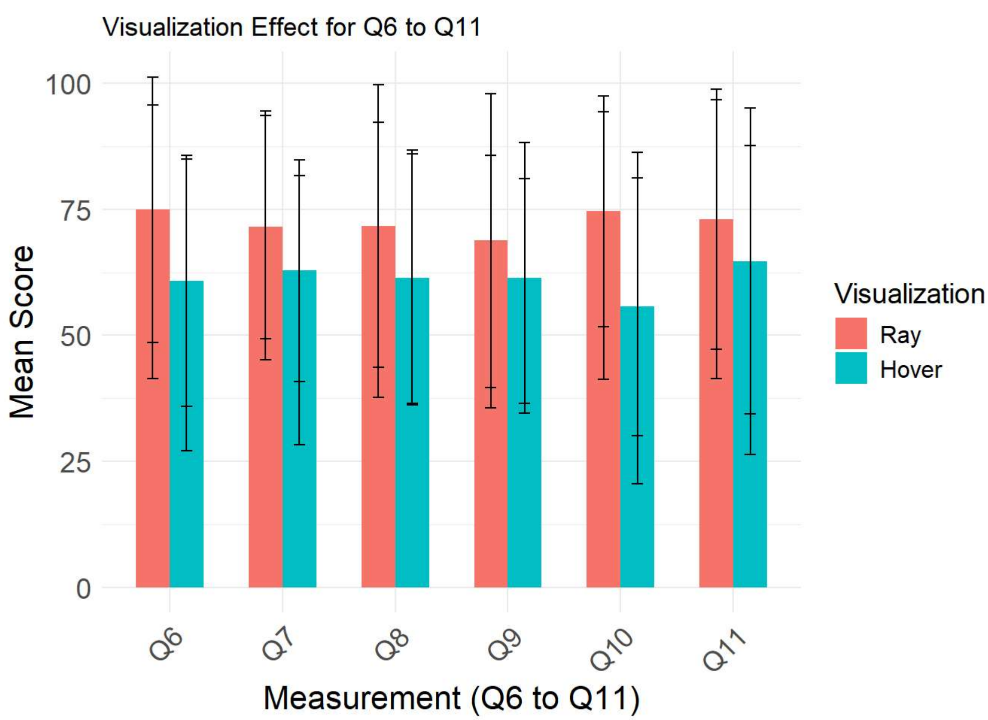
```
## Response: art(score)
##
##                                      F Df Df.res  Pr(>F)
## 1 Directionality               0.95925  1     60 0.33131
## 2 Visualization                2.24666  1     60 0.13915
## 3 Directionality:Visualization 0.58028  1     60 0.44919
## ---
## Signif. codes:   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Analyzing Q3_9
## Analysis of Variance of Aligned Rank Transformed Data
##
## Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)
## Model: Mixed Effects (lmer)
## Response: art(score)
##
##                                     F Df Df.res   Pr(>F)
## 1 Directionality               1.0093  1     60 0.319108
## 2 Visualization                1.2610  1     60 0.265938
## 3 Directionality:Visualization 3.3588  1     60 0.071812 .
## ---
## Signif. codes:   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Analyzing Q3_10
## Analysis of Variance of Aligned Rank Transformed Data
##
## Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)
## Model: Mixed Effects (lmer)
## Response: art(score)
##
##                                      F Df Df.res    Pr(>F)
## 1 Directionality               0.41009  1     60 0.5243641
## 2 Visualization                8.26193  1     60 0.0055932 **
## 3 Directionality:Visualization 0.29364  1     60 0.5899050
## ---
## Signif. codes:   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Analyzing Q3_11
## Analysis of Variance of Aligned Rank Transformed Data
##
## Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)
## Model: Mixed Effects (lmer)
## Response: art(score)
##
##                                     F Df Df.res   Pr(>F)
## 1 Directionality               0.1828  1     60 0.670512
## 2 Visualization                3.4003  1     60 0.070124 .
## 3 Directionality:Visualization 1.3675  1     60 0.246868
## ---
## Signif. codes:   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

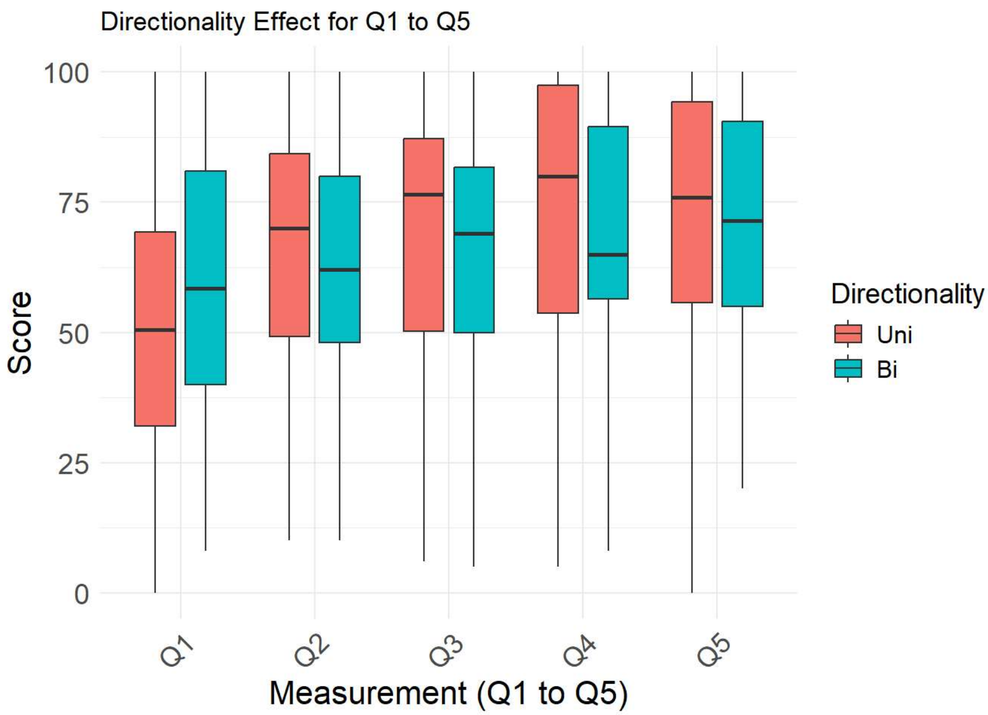
```
## # A tibble: 44 × 5
##    Measurement Directionality Visualization  mean    sd
##    <fct>       <fct>          <fct>         <dbl> <dbl>
##  1 Q1          Uni            Ray            57.4  28.3
##  2 Q1          Uni            Hover          43.9  23.1
##  3 Q1          Bi             Ray            64.6  26.1
##  4 Q1          Bi             Hover          54.5  26.5
##  5 Q2          Uni            Ray            75.6  25.7
##  6 Q2          Uni            Hover          58.0  21.9
##  7 Q2          Bi             Ray            69.7  25.1
##  8 Q2          Bi             Hover          53.9  25.1
##  9 Q3          Uni            Ray            76.1  21.8
## 10 Q3          Uni            Hover          59.7  25.4
## 11 Q3          Bi             Ray            71.5  26.0
## 12 Q3          Bi             Hover          56.1  24.7
## 13 Q4          Uni            Ray            80.8  19.8
## 14 Q4          Uni            Hover          67.7  27.0
## 15 Q4          Bi             Ray            71.8  23.3
## 16 Q4          Bi             Hover          62.7  27.5
## 17 Q5          Uni            Ray            77    24.0
## 18 Q5          Uni            Hover          65.6  27.0
## 19 Q5          Bi             Ray            74.5  22.0
## 20 Q5          Bi             Hover          65.6  23.0
## 21 Q6          Uni            Ray            75.0  26.4
## 22 Q6          Uni            Hover          60.8  24.9
## 23 Q6          Bi             Ray            68.5  27.2
## 24 Q6          Bi             Hover          56.0  28.9
## 25 Q7          Uni            Ray            69.9  24.7
## 26 Q7          Uni            Hover          62.9  22.0
## 27 Q7          Bi             Ray            71.5  22.2
## 28 Q7          Bi             Hover          55    26.7
## 29 Q8          Uni            Ray            65.0  27.3
## 30 Q8          Uni            Hover          61.2  24.8
## 31 Q8          Bi             Ray            71.7  28.0
## 32 Q8          Bi             Hover          61.5  25.2
## 33 Q9          Uni            Ray            60.7  25.1
## 34 Q9          Uni            Hover          61.4  26.8
## 35 Q9          Bi             Ray            68.8  29.2
## 36 Q9          Bi             Hover          58.8  22.3
## 37 Q10         Uni            Ray            74.6  22.8
## 38 Q10         Uni            Hover          55.7  25.6
## 39 Q10         Bi             Ray            67.9  26.6
## 40 Q10         Bi             Hover          53.4  32.9
## 41 Q11         Uni            Ray            73.0  25.8
## 42 Q11         Uni            Hover          57    30.6
## 43 Q11         Bi             Ray            69.1  27.6
## 44 Q11         Bi             Hover          64.8  30.4
```

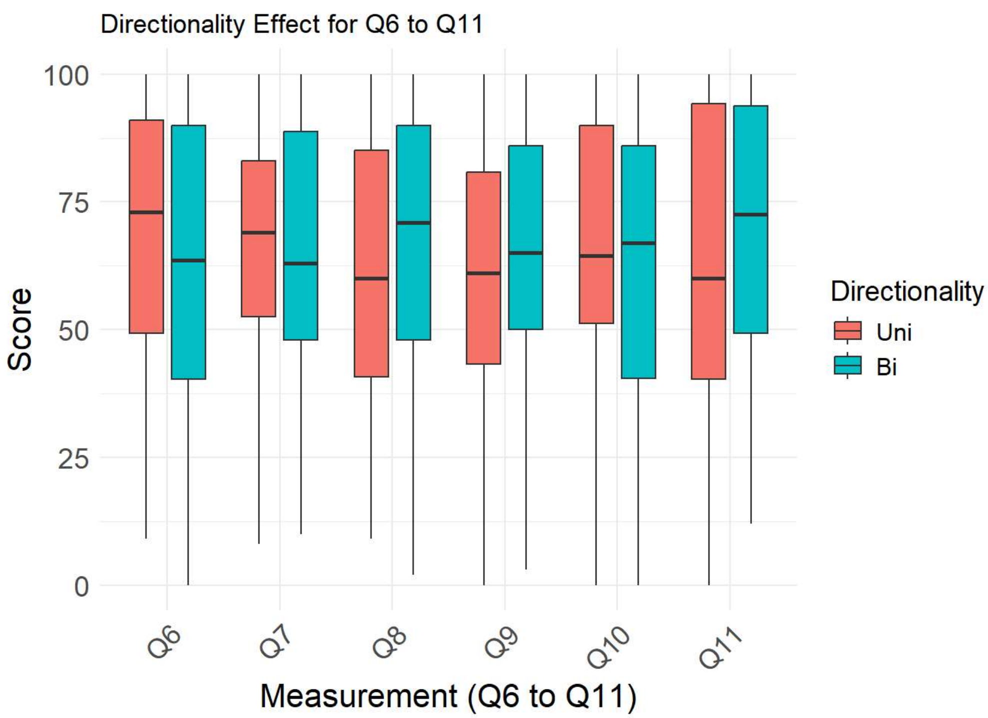

Directionality Effect for Q1 to Q5
100
75
50
25
0
Mean Score
Q1
Q2
Q3
Q4
Q5
Measurement (Q1 to Q5)
Directionality
Uni
Bi

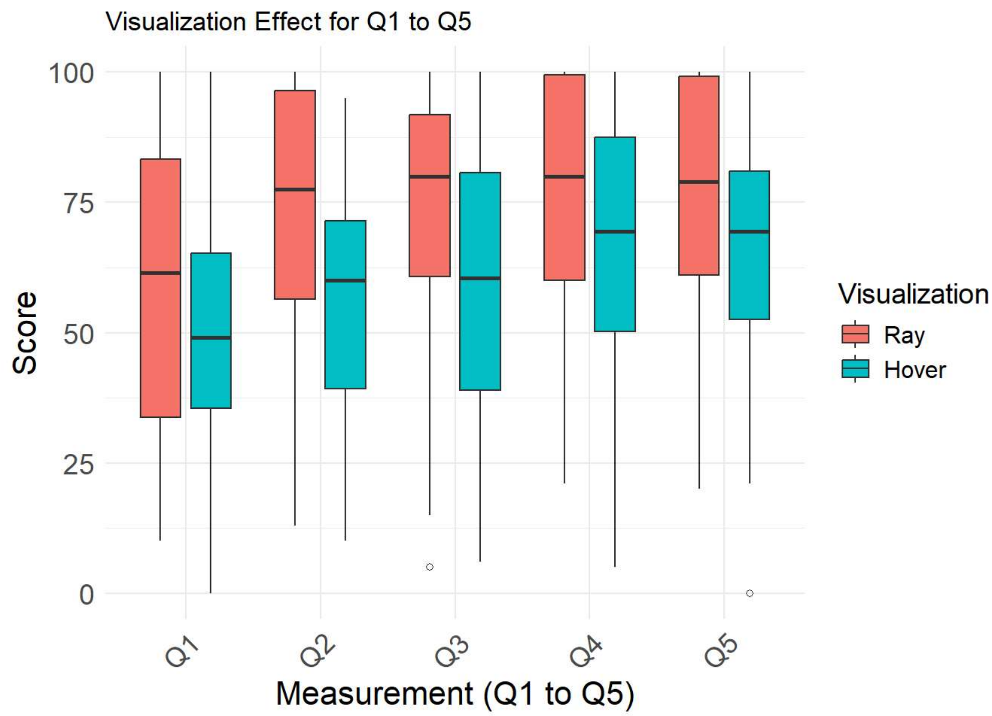

Directionality Effect for Q6 to Q11
100
75
50
25
0
Mean Score
Q6
Q7
Q8
Q9
Q10
Q11
Measurement (Q6 to Q11)
Directionality
Uni
Bi

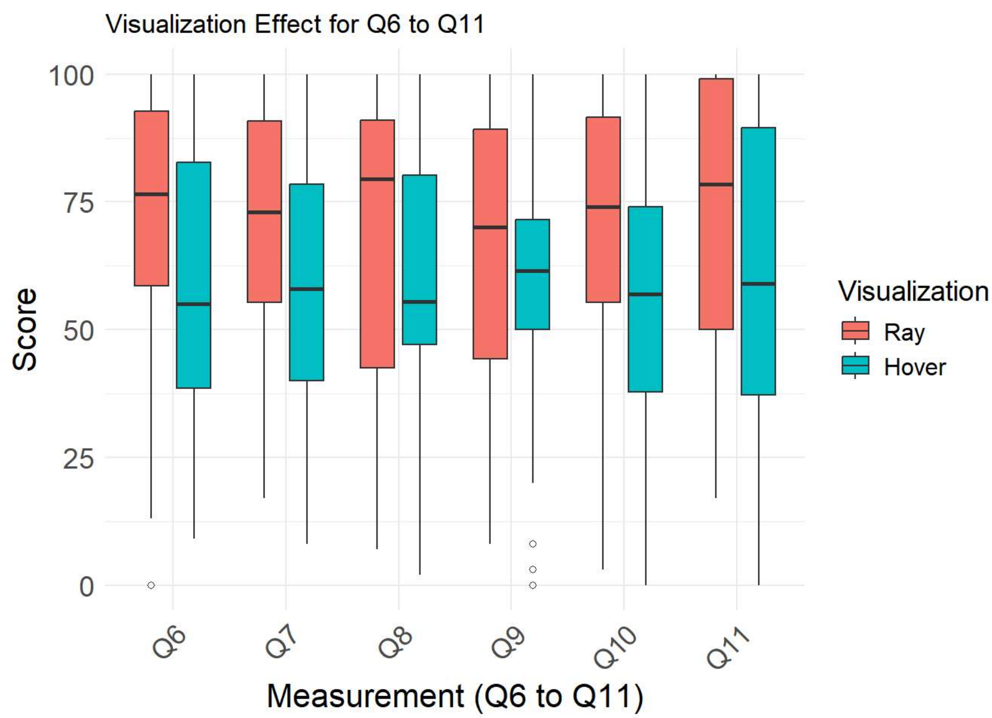

Visualization Effect for Q1 to Q5
Mean Score
100
75
50
25
0
Q1
Q2
Q3
Q4
Q5
Measurement (Q1 to Q5)
Visualization
Ray
Hover

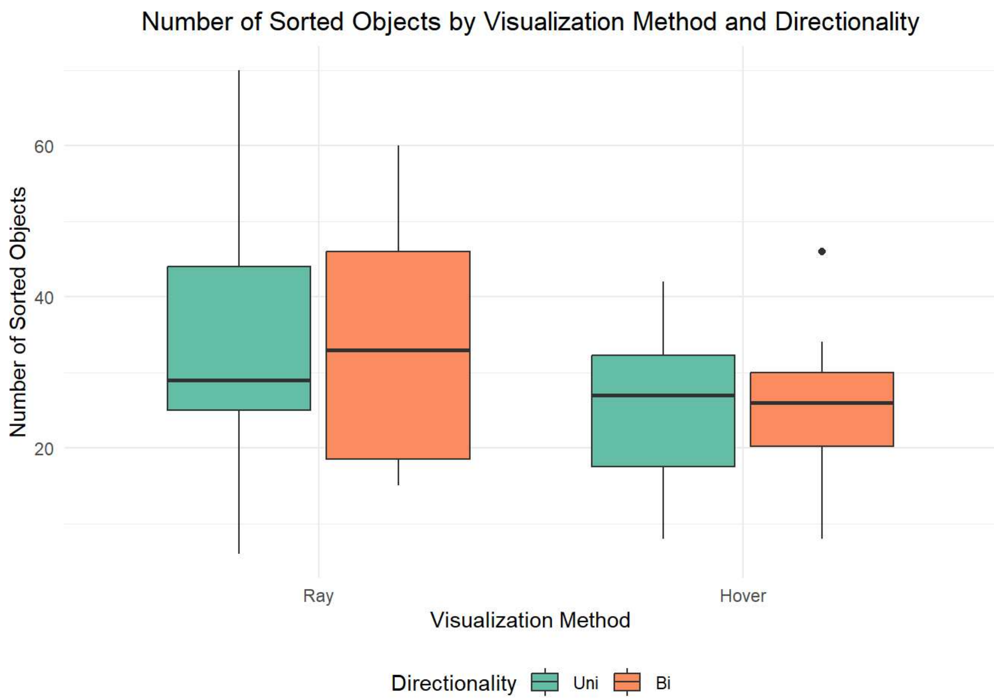

Visualization Effect for Q6 to Q11
Mean Score
100
75
50
25
0
Q6
Q7
Q8
Q9
Q10
Q11
Measurement (Q6 to Q11)
Visualization
Ray
Hover


Directionality Effect for Q1 to Q5
100
75
50
25
0
Score
Q1
Q2
Q3
Q4
Q5
Measurement (Q1 to Q5)
Directionality
Uni
Bi


Directionality Effect for Q6 to Q11
100
75
50
25
0
Score
Q6
Q7
Q8
Q9
Q10
Q11
Measurement (Q6 to Q11)
Directionality
Uni
Bi

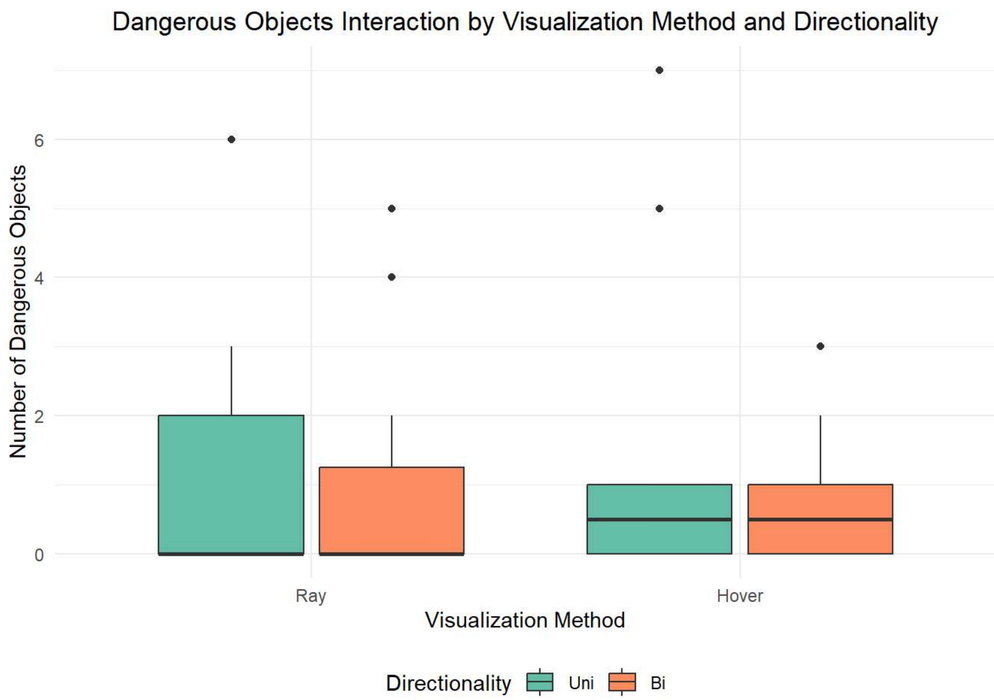

Visualization Effect for Q1 to Q5
100
75
50
25
0
Score
Q1
Q2
Q3
Q4
Q5
Measurement (Q1 to Q5)
Visualization
Ray
Hover


Visualization Effect for Q6 to Q11
100
75
50
25
0
Score
Q6
Q7
Q8
Q9
Q10
Q11
Measurement (Q6 to Q11)
Visualization
Ray
Hover




```
## $ANOVA
##                         Effect DFn DFd         SSn       SSd           F
## 1                  (Intercept)   1  11 41949.18750 5245.0625 87.97627531
## 2                Visualization   1  11   892.68750 1702.5625  5.76751955
## 3               Directionality   1  11    11.02083  740.2292  0.16377248
## 4 Visualization:Directionality   1  11     4.68750 1011.5625  0.05097312
##              p p<.05          ges
## 1 1.396731e-06     * 0.8282397549
## 2 3.513506e-02     * 0.0930648255
## 3 6.934648e-01       0.0012652445
## 4 8.255185e-01       0.0005385391
```

```
## # A tibble: 4 × 5
## # Groups:   Visualization [2]
##   Visualization Directionality  Mean    SD     N
##   <fct>         <fct>          <dbl> <dbl> <int>
## 1 Ray           Uni             34.7  18.2    12
## 2 Ray           Bi              33.1  15.6    12
## 3 Hover         Uni             25.4  10.4    12
## 4 Hover         Bi              25.1  10.4    12
```




```
## $ANOVA
##                         Effect DFn DFd         SSn      SSd           F
## 1                  (Intercept)   1  11 54.18750000 68.06250 8.757575758
## 2                Visualization   1  11  0.02083333 25.22917 0.009083402
## 3               Directionality   1  11  1.02083333 25.22917 0.445086705
## 4 Visualization:Directionality   1  11  1.02083333 20.22917 0.555097837
##            p p<.05          ges
## 1 0.01299107     * 0.3231055901
## 2 0.92578514       0.0001834862
## 3 0.51842760       0.0089123318
## 4 0.47186134       0.0089123318
```

```
## # A tibble: 4 × 5
## # Groups:   Visualization [2]
##   Visualization Directionality  Mean    SD     N
##   <fct>         <fct>          <dbl> <dbl> <int>
## 1 Ray           Uni             1.08 1.88     12
## 2 Ray           Bi              1.08 1.73     12
## 3 Hover         Uni             1.33 2.27     12
## 4 Hover         Bi              0.75 0.965    12
```

```
## Aligned Rank Transform of Factorial Model
##
## Call:
## art(formula = num_sorted_objects ~ Visualization * Directionality +
##     Error(subject/(Visualization * Directionality)), data = data)
##
## Column sums of aligned responses (should all be ~0):
##               Visualization              Directionality
##                           0                           0
## Visualization:Directionality
##                           0
##
## F values of ANOVAs on aligned responses not of interest (should all be ~0):
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##       0       0       0       0       0       0
```

```
## Analysis of Variance of Aligned Rank Transformed Data
##
## Table Type: Repeated Measures Analysis of Variance Table (Type I)
## Model: Repeated Measures (aov)
## Response: art(num_sorted_objects)
##
##                                Error Df Df.res  F value   Pr(>F)
## 1 Visualization                sbj:V  1     11 3.869551 0.074899 .
## 2 Directionality               sbj:D  1     11 0.211238 0.654749
## 3 Visualization:Directionality s:V:D  1     11 0.019422 0.891682
## ---
## Signif. codes:   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
## # A tibble: 4 × 5
## # Groups:   Visualization [2]
##   Visualization Directionality  Mean    SD     N
##   <fct>         <fct>          <dbl> <dbl> <int>
## 1 Ray           Uni             34.7  18.2    12
## 2 Ray           Bi              33.1  15.6    12
## 3 Hover         Uni             25.4  10.4    12
## 4 Hover         Bi              25.1  10.4    12
```

APPENDIX E

STATISTICAL ANALYSIS: THE SOCIAL EFFECTS OF SHARED-GAZE VISUALIZATIONS IN AN INDUSTRIAL SORTING TASK WITH VISUAL CUES

sgv-sound

2025-04-29

R Markdown

```
## Warning: package 'ARTool' was built under R version 4.4.2
```

```
## Welcome to emmeans.
## Caution: You lose important information if you filter this package's results.
## See '? untidy'
```

```
##
## Attaching package: 'dplyr'
```

```
## The following objects are masked from 'package:stats':
##
##     filter, lag
```

```
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
## Analysis of Variance of Aligned Rank Transformed Data
##
## Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)
## Model: Mixed Effects (lmer)
## Response: art(Q3_1)
##
##                              F Df Df.res  Pr(>F)
## 1 sound               1.84362  1     38 0.18254
## 2 visualization       0.12419  2     76 0.88339
## 3 sound:visualization 1.81183  2     76 0.17034
## ---
## Signif. codes:   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## $emmeans
##  sound visualization emmean   SE   df lower.CL upper.CL
##  0     1               58.8 7.88 65.3     43.1     74.5
##  1     1               57.1 7.88 65.3     41.4     72.8
##  0     2               65.0 7.88 65.3     49.3     80.7
##  1     2               54.4 7.88 65.3     38.7     70.1
##  0     3               59.8 7.88 65.3     44.1     75.5
##  1     3               67.9 7.88 65.3     52.2     83.6
##
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
## $contrasts
##  contrast                                      estimate    SE   df t.ratio
##  sound0 visualization1 - sound1 visualization1      1.7 11.10 65.3   0.153
##  sound0 visualization1 - sound0 visualization2     -6.2  6.95 76.0  -0.892
##  sound0 visualization1 - sound1 visualization2      4.4 11.10 65.3   0.395
##  sound0 visualization1 - sound0 visualization3     -1.0  6.95 76.0  -0.144
##  sound0 visualization1 - sound1 visualization3     -9.1 11.10 65.3  -0.817
##  sound1 visualization1 - sound0 visualization2     -7.9 11.10 65.3  -0.709
##  sound1 visualization1 - sound1 visualization2      2.7  6.95 76.0   0.389
##  sound1 visualization1 - sound0 visualization3     -2.7 11.10 65.3  -0.242
##  sound1 visualization1 - sound1 visualization3    -10.8  6.95 76.0  -1.554
##  sound0 visualization2 - sound1 visualization2     10.6 11.10 65.3   0.952
##  sound0 visualization2 - sound0 visualization3      5.2  6.95 76.0   0.748
##  sound0 visualization2 - sound1 visualization3     -2.9 11.10 65.3  -0.260
##  sound1 visualization2 - sound0 visualization3     -5.4 11.10 65.3  -0.485
##  sound1 visualization2 - sound1 visualization3    -13.5  6.95 76.0  -1.943
##  sound0 visualization3 - sound1 visualization3     -8.1 11.10 65.3  -0.727
##  p.value
##   1.0000
##   0.9473
##   0.9987
##   1.0000
##   0.9634
##   0.9802
##   0.9988
##   0.9999
##   0.6307
##   0.9312
```

```
##   0.9750
##   0.9998
##   0.9965
##   0.3848
##   0.9779
##
## Degrees-of-freedom method: kenward-roger
## P value adjustment: tukey method for comparing a family of 6 estimates
##
## Analysis of Variance of Aligned Rank Transformed Data
##
## Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)
## Model: Mixed Effects (lmer)
## Response: art(Q3_2)
##
##                           F Df Df.res   Pr(>F)
## 1 sound              2.6209  1     38 0.113737
## 2 visualization      1.2646  2     76 0.288231
## 3 sound:visualization 4.5933  2     76 0.013086 *
## ---
## Signif. codes:   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## $emmeans
##  sound visualization emmean   SE   df lower.CL upper.CL
##  0     1               59.9 7.79 66.7     44.4     75.4
##  1     1               56.8 7.79 66.7     41.3     72.3
##  0     2               67.1 7.79 66.7     51.6     82.6
##  1     2               49.8 7.79 66.7     34.3     65.3
##  0     3               58.4 7.79 66.7     42.8     73.9
##  1     3               71.0 7.79 66.7     55.5     86.6
##
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
## $contrasts
##  contrast                                      estimate SE   df t.ratio p.value
##  sound0 visualization1 - sound1 visualization1     3.10 11 66.7   0.282  0.9998
##  sound0 visualization1 - sound0 visualization2    -7.20  7 76.0  -1.028  0.9070
##  sound0 visualization1 - sound1 visualization2    10.10 11 66.7   0.917  0.9407
##  sound0 visualization1 - sound0 visualization3     1.55  7 76.0   0.221  0.9999
##  sound0 visualization1 - sound1 visualization3   -11.15 11 66.7  -1.013  0.9121
##  sound1 visualization1 - sound0 visualization2   -10.30 11 66.7  -0.935  0.9358
##  sound1 visualization1 - sound1 visualization2     7.00  7 76.0   1.000  0.9166
##  sound1 visualization1 - sound0 visualization3    -1.55 11 66.7  -0.141  1.0000
##  sound1 visualization1 - sound1 visualization3   -14.25  7 76.0  -2.035  0.3326
##  sound0 visualization2 - sound1 visualization2    17.30 11 66.7   1.571  0.6200
##  sound0 visualization2 - sound0 visualization3     8.75  7 76.0   1.250  0.8108
##  sound0 visualization2 - sound1 visualization3    -3.95 11 66.7  -0.359  0.9992
##  sound1 visualization2 - sound0 visualization3    -8.55 11 66.7  -0.777  0.9706
##  sound1 visualization2 - sound1 visualization3   -21.25  7 76.0  -3.035  0.0373
##  sound0 visualization3 - sound1 visualization3   -12.70 11 66.7  -1.153  0.8569
##
## Degrees-of-freedom method: kenward-roger
```

```
## P value adjustment: tukey method for comparing a family of 6 estimates
##
## Analysis of Variance of Aligned Rank Transformed Data
##
## Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)
## Model: Mixed Effects (lmer)
## Response: art(Q3_3)
##
##                            F Df Df.res   Pr(>F)
## 1 sound               1.5740  1     38 0.217289
## 2 visualization       2.7395  2     76 0.070984 .
## 3 sound:visualization 1.5596  2     76 0.216869
## ---
## Signif. codes:   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## $emmeans
##  sound visualization emmean   SE   df lower.CL upper.CL
##  0     1              59.9 7.86 72.3     44.2     75.5
##  1     1              53.7 7.86 72.3     38.0     69.4
##  0     2              64.8 7.86 72.3     49.1     80.4
##  1     2              55.6 7.86 72.3     39.9     71.3
##  0     3              60.3 7.86 72.3     44.6     76.0
##  1     3              68.8 7.86 72.3     53.1     84.5
##
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
## $contrasts
##  contrast                                      estimate    SE   df t.ratio
##  sound0 visualization1 - sound1 visualization1     6.15 11.10 72.3   0.553
##  sound0 visualization1 - sound0 visualization2    -4.90  7.56 76.0  -0.648
##  sound0 visualization1 - sound1 visualization2     4.25 11.10 72.3   0.382
##  sound0 visualization1 - sound0 visualization3    -0.45  7.56 76.0  -0.060
##  sound0 visualization1 - sound1 visualization3    -8.95 11.10 72.3  -0.805
##  sound1 visualization1 - sound0 visualization2   -11.05 11.10 72.3  -0.994
##  sound1 visualization1 - sound1 visualization2    -1.90  7.56 76.0  -0.251
##  sound1 visualization1 - sound0 visualization3    -6.60 11.10 72.3  -0.594
##  sound1 visualization1 - sound1 visualization3   -15.10  7.56 76.0  -1.997
##  sound0 visualization2 - sound1 visualization2     9.15 11.10 72.3   0.823
##  sound0 visualization2 - sound0 visualization3     4.45  7.56 76.0   0.588
##  sound0 visualization2 - sound1 visualization3    -4.05 11.10 72.3  -0.364
##  sound1 visualization2 - sound0 visualization3    -4.70 11.10 72.3  -0.423
##  sound1 visualization2 - sound1 visualization3   -13.20  7.56 76.0  -1.746
##  sound0 visualization3 - sound1 visualization3    -8.50 11.10 72.3  -0.765
##  p.value
##   0.9936
##   0.9868
##   0.9989
##   1.0000
##   0.9657
##   0.9183
##   0.9999
##   0.9911
```

```
##   0.3538
##   0.9623
##   0.9915
##   0.9991
##   0.9982
##   0.5067
##   0.9725
##
## Degrees-of-freedom method: kenward-roger
## P value adjustment: tukey method for comparing a family of 6 estimates
##
## Analysis of Variance of Aligned Rank Transformed Data
##
## Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)
## Model: Mixed Effects (lmer)
## Response: art(Q3_4)
##
##                            F Df Df.res  Pr(>F)
## 1 sound               2.3289  1     38 0.13528
## 2 visualization       1.7851  2     76 0.17474
## 3 sound:visualization 2.3730  2     76 0.10007
## ---
## Signif. codes:   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## $emmeans
##  sound visualization emmean   SE   df lower.CL upper.CL
##  0     1               59.2 7.84 65.6     43.6     74.9
##  1     1               53.6 7.84 65.6     38.0     69.3
##  0     2               61.5 7.84 65.6     45.9     77.2
##  1     2               57.9 7.84 65.6     42.2     73.5
##  0     3               58.5 7.84 65.6     42.8     74.1
##  1     3               72.2 7.84 65.6     56.6     87.9
##
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
## $contrasts
##  contrast                                      estimate    SE   df t.ratio
##  sound0 visualization1 - sound1 visualization1      5.6 11.10 65.6   0.505
##  sound0 visualization1 - sound0 visualization2     -2.3  6.94 76.0  -0.331
##  sound0 visualization1 - sound1 visualization2      1.4 11.10 65.6   0.126
##  sound0 visualization1 - sound0 visualization3      0.8  6.94 76.0   0.115
##  sound0 visualization1 - sound1 visualization3    -13.0 11.10 65.6  -1.173
##  sound1 visualization1 - sound0 visualization2     -7.9 11.10 65.6  -0.713
##  sound1 visualization1 - sound1 visualization2     -4.2  6.94 76.0  -0.605
##  sound1 visualization1 - sound0 visualization3     -4.8 11.10 65.6  -0.433
##  sound1 visualization1 - sound1 visualization3    -18.6  6.94 76.0  -2.679
##  sound0 visualization2 - sound1 visualization2      3.7 11.10 65.6   0.334
##  sound0 visualization2 - sound0 visualization3      3.1  6.94 76.0   0.447
##  sound0 visualization2 - sound1 visualization3    -10.7 11.10 65.6  -0.966
##  sound1 visualization2 - sound0 visualization3     -0.6 11.10 65.6  -0.054
##  sound1 visualization2 - sound1 visualization3    -14.4  6.94 76.0  -2.074
##  sound0 visualization3 - sound1 visualization3    -13.8 11.10 65.6  -1.245
```

```
##  p.value
##   0.9958
##   0.9995
##   1.0000
##   1.0000
##   0.8479
##   0.9797
##   0.9904
##   0.9980
##   0.0914
##   0.9994
##   0.9977
##   0.9271
##   1.0000
##   0.3117
##   0.8128
##
## Degrees-of-freedom method: kenward-roger
## P value adjustment: tukey method for comparing a family of 6 estimates
##
## Analysis of Variance of Aligned Rank Transformed Data
##
## Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)
## Model: Mixed Effects (lmer)
## Response: art(Q3_5)
##
##                            F Df Df.res   Pr(>F)
## 1 sound               2.6481  1     38 0.111939
## 2 visualization       1.6640  2     76 0.196201
## 3 sound:visualization 2.7712  2     76 0.068919 .
## ---
## Signif. codes:   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## $emmeans
##  sound visualization emmean   SE   df lower.CL upper.CL
##  0     1               58.4 7.84 60.2     42.7     74.1
##  1     1               54.6 7.84 60.2     39.0     70.3
##  0     2               62.6 7.84 60.2     46.9     78.3
##  1     2               57.0 7.84 60.2     41.4     72.7
##  0     3               58.3 7.84 60.2     42.6     74.0
##  1     3               72.0 7.84 60.2     56.3     87.7
##
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
## $contrasts
##  contrast                                      estimate    SE   df t.ratio
##  sound0 visualization1 - sound1 visualization1     3.75 11.10 60.2   0.338
##  sound0 visualization1 - sound0 visualization2    -4.20  6.39 76.0  -0.658
##  sound0 visualization1 - sound1 visualization2     1.35 11.10 60.2   0.122
##  sound0 visualization1 - sound0 visualization3     0.10  6.39 76.0   0.016
##  sound0 visualization1 - sound1 visualization3   -13.60 11.10 60.2  -1.227
##  sound1 visualization1 - sound0 visualization2    -7.95 11.10 60.2  -0.717
```

```
##  sound1 visualization1 - sound1 visualization2    -2.40  6.39 76.0  -0.376
##  sound1 visualization1 - sound0 visualization3    -3.65 11.10 60.2  -0.329
##  sound1 visualization1 - sound1 visualization3   -17.35  6.39 76.0  -2.716
##  sound0 visualization2 - sound1 visualization2     5.55 11.10 60.2   0.501
##  sound0 visualization2 - sound0 visualization3     4.30  6.39 76.0   0.673
##  sound0 visualization2 - sound1 visualization3    -9.40 11.10 60.2  -0.848
##  sound1 visualization2 - sound0 visualization3    -1.25 11.10 60.2  -0.113
##  sound1 visualization2 - sound1 visualization3   -14.95  6.39 76.0  -2.341
##  sound0 visualization3 - sound1 visualization3   -13.70 11.10 60.2  -1.236
##  p.value
##   0.9994
##   0.9859
##   1.0000
##   1.0000
##   0.8221
##   0.9791
##   0.9990
##   0.9995
##   0.0837
##   0.9960
##   0.9844
##   0.9571
##   1.0000
##   0.1910
##   0.8176
##
## Degrees-of-freedom method: kenward-roger
## P value adjustment: tukey method for comparing a family of 6 estimates
##
## Analysis of Variance of Aligned Rank Transformed Data
##
## Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)
## Model: Mixed Effects (lmer)
## Response: art(Q3_6)
##
##                             F Df Df.res  Pr(>F)
## 1 sound               2.66900  1     38 0.11058
## 2 visualization       0.93329  2     76 0.39772
## 3 sound:visualization 1.16604  2     76 0.31711
## ---
## Signif. codes:   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## $emmeans
##  sound visualization emmean   SE   df lower.CL upper.CL
##  0     1               58.7 7.88 69.5     43.0     74.4
##  1     1               54.5 7.88 69.5     38.8     70.3
##  0     2               65.7 7.88 69.5     50.0     81.4
##  1     2               57.7 7.88 69.5     42.0     73.4
##  0     3               59.5 7.88 69.5     43.8     75.3
##  1     3               66.8 7.88 69.5     51.1     82.5
##
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
```

```
##
## $contrasts
##  contrast                                      estimate    SE   df t.ratio
##  sound0 visualization1 - sound1 visualization1     4.15 11.10 69.5   0.372
##  sound0 visualization1 - sound0 visualization2    -7.00  7.34 76.0  -0.953
##  sound0 visualization1 - sound1 visualization2     1.00 11.10 69.5   0.090
##  sound0 visualization1 - sound0 visualization3    -0.85  7.34 76.0  -0.116
##  sound0 visualization1 - sound1 visualization3    -8.10 11.10 69.5  -0.727
##  sound1 visualization1 - sound0 visualization2   -11.15 11.10 69.5  -1.000
##  sound1 visualization1 - sound1 visualization2    -3.15  7.34 76.0  -0.429
##  sound1 visualization1 - sound0 visualization3    -5.00 11.10 69.5  -0.449
##  sound1 visualization1 - sound1 visualization3   -12.25  7.34 76.0  -1.668
##  sound0 visualization2 - sound1 visualization2     8.00 11.10 69.5   0.718
##  sound0 visualization2 - sound0 visualization3     6.15  7.34 76.0   0.837
##  sound0 visualization2 - sound1 visualization3    -1.10 11.10 69.5  -0.099
##  sound1 visualization2 - sound0 visualization3    -1.85 11.10 69.5  -0.166
##  sound1 visualization2 - sound1 visualization3    -9.10  7.34 76.0  -1.239
##  sound0 visualization3 - sound1 visualization3    -7.25 11.10 69.5  -0.650
##  p.value
##   0.9990
##   0.9310
##   1.0000
##   1.0000
##   0.9780
##   0.9163
##   0.9981
##   0.9976
##   0.5569
##   0.9792
##   0.9595
##   1.0000
##   1.0000
##   0.8162
##   0.9866
##
## Degrees-of-freedom method: kenward-roger
## P value adjustment: tukey method for comparing a family of 6 estimates
##
## Analysis of Variance of Aligned Rank Transformed Data
##
## Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)
## Model: Mixed Effects (lmer)
## Response: art(Q3_7)
##
##                              F Df Df.res  Pr(>F)
## 1 sound               2.3750  1     38 0.13158
## 2 visualization       1.4523  2     76 0.24044
## 3 sound:visualization 1.7359  2     76 0.18316
## ---
## Signif. codes:   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## $emmeans
##  sound visualization emmean   SE   df lower.CL upper.CL
```

```
##  0     1              59.5 7.87 75.1     43.8     75.1
##  1     1              55.6 7.87 75.1     40.0     71.3
##  0     2              68.3 7.87 75.1     52.7     84.0
##  1     2              57.1 7.87 75.1     41.5     72.8
##  0     3              56.6 7.87 75.1     41.0     72.3
##  1     3              65.8 7.87 75.1     50.1     81.4
##
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
## $contrasts
##  contrast                                      estimate   SE   df t.ratio
##  sound0 visualization1 - sound1 visualization1      3.8 11.1 75.1   0.341
##  sound0 visualization1 - sound0 visualization2     -8.9  7.8 76.0  -1.141
##  sound0 visualization1 - sound1 visualization2      2.3 11.1 75.1   0.207
##  sound0 visualization1 - sound0 visualization3      2.8  7.8 76.0   0.359
##  sound0 visualization1 - sound1 visualization3     -6.3 11.1 75.1  -0.566
##  sound1 visualization1 - sound0 visualization2    -12.7 11.1 75.1  -1.141
##  sound1 visualization1 - sound1 visualization2     -1.5  7.8 76.0  -0.192
##  sound1 visualization1 - sound0 visualization3     -1.0 11.1 75.1  -0.090
##  sound1 visualization1 - sound1 visualization3    -10.1  7.8 76.0  -1.295
##  sound0 visualization2 - sound1 visualization2     11.2 11.1 75.1   1.006
##  sound0 visualization2 - sound0 visualization3     11.7  7.8 76.0   1.500
##  sound0 visualization2 - sound1 visualization3      2.6 11.1 75.1   0.234
##  sound1 visualization2 - sound0 visualization3      0.5 11.1 75.1   0.045
##  sound1 visualization2 - sound1 visualization3     -8.6  7.8 76.0  -1.103
##  sound0 visualization3 - sound1 visualization3     -9.1 11.1 75.1  -0.818
##  p.value
##   0.9994
##   0.8624
##   0.9999
##   0.9992
##   0.9929
##   0.8625
##   1.0000
##   1.0000
##   0.7867
##   0.9144
##   0.6650
##   0.9999
##   1.0000
##   0.8787
##   0.9634
##
## Degrees-of-freedom method: kenward-roger
## P value adjustment: tukey method for comparing a family of 6 estimates
##
## Analysis of Variance of Aligned Rank Transformed Data
##
## Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)
## Model: Mixed Effects (lmer)
## Response: art(Q3_8)
```

```
##
##                                F Df Df.res  Pr(>F)
## 1 sound               3.53227520  1     38 0.06787 .
## 2 visualization       0.00016738  2     76 0.99983
## 3 sound:visualization 0.30376884  2     76 0.73892
## ---
## Signif. codes:   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## $emmeans
##  sound visualization emmean   SE   df lower.CL upper.CL
##  0     1               62.6 7.93 61.2     46.7     78.5
##  1     1               59.2 7.93 61.2     43.3     75.1
##  0     2               58.2 7.93 61.2     42.4     74.1
##  1     2               59.6 7.93 61.2     43.8     75.5
##  0     3               59.8 7.93 61.2     43.9     75.7
##  1     3               63.5 7.93 61.2     47.6     79.4
##
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
## $contrasts
##  contrast                                      estimate    SE   df t.ratio
##  sound0 visualization1 - sound1 visualization1     3.40 11.20 61.2   0.303
##  sound0 visualization1 - sound0 visualization2     4.35  6.57 76.0   0.662
##  sound0 visualization1 - sound1 visualization2     2.95 11.20 61.2   0.263
##  sound0 visualization1 - sound0 visualization3     2.80  6.57 76.0   0.426
##  sound0 visualization1 - sound1 visualization3    -0.90 11.20 61.2  -0.080
##  sound1 visualization1 - sound0 visualization2     0.95 11.20 61.2   0.085
##  sound1 visualization1 - sound1 visualization2    -0.45  6.57 76.0  -0.068
##  sound1 visualization1 - sound0 visualization3    -0.60 11.20 61.2  -0.053
##  sound1 visualization1 - sound1 visualization3    -4.30  6.57 76.0  -0.654
##  sound0 visualization2 - sound1 visualization2    -1.40 11.20 61.2  -0.125
##  sound0 visualization2 - sound0 visualization3    -1.55  6.57 76.0  -0.236
##  sound0 visualization2 - sound1 visualization3    -5.25 11.20 61.2  -0.468
##  sound1 visualization2 - sound0 visualization3    -0.15 11.20 61.2  -0.013
##  sound1 visualization2 - sound1 visualization3    -3.85  6.57 76.0  -0.586
##  sound0 visualization3 - sound1 visualization3    -3.70 11.20 61.2  -0.330
##  p.value
##   0.9996
##   0.9855
##   0.9998
##   0.9981
##   1.0000
##   1.0000
##   1.0000
##   1.0000
##   0.9863
##   1.0000
##   0.9999
##   0.9971
##   1.0000
##   0.9917
##   0.9995
```

```
##
## Degrees-of-freedom method: kenward-roger
## P value adjustment: tukey method for comparing a family of 6 estimates
##
## Analysis of Variance of Aligned Rank Transformed Data
##
## Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)
## Model: Mixed Effects (lmer)
## Response: art(Q3_9)
##
##                              F Df Df.res   Pr(>F)
## 1 sound                3.970788  1     38 0.053514 .
## 2 visualization        0.218550  2     76 0.804187
## 3 sound:visualization 0.017868  2     76 0.982294
## ---
## Signif. codes:   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## $emmeans
##  sound visualization emmean   SE   df lower.CL upper.CL
##  0     1               59.9 7.94 60.7     44.0     75.7
##  1     1               61.0 7.94 60.7     45.1     76.8
##  0     2               58.9 7.94 60.7     43.0     74.8
##  1     2               58.6 7.94 60.7     42.7     74.5
##  0     3               61.7 7.94 60.7     45.8     77.6
##  1     3               63.0 7.94 60.7     47.1     78.9
##
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
## $contrasts
##  contrast                                      estimate    SE   df t.ratio
##  sound0 visualization1 - sound1 visualization1    -1.10 11.20 60.7  -0.098
##  sound0 visualization1 - sound0 visualization2     0.95  6.52 76.0   0.146
##  sound0 visualization1 - sound1 visualization2     1.25 11.20 60.7   0.111
##  sound0 visualization1 - sound0 visualization3    -1.85  6.52 76.0  -0.284
##  sound0 visualization1 - sound1 visualization3    -3.15 11.20 60.7  -0.281
##  sound1 visualization1 - sound0 visualization2     2.05 11.20 60.7   0.183
##  sound1 visualization1 - sound1 visualization2     2.35  6.52 76.0   0.360
##  sound1 visualization1 - sound0 visualization3    -0.75 11.20 60.7  -0.067
##  sound1 visualization1 - sound1 visualization3    -2.05  6.52 76.0  -0.314
##  sound0 visualization2 - sound1 visualization2     0.30 11.20 60.7   0.027
##  sound0 visualization2 - sound0 visualization3    -2.80  6.52 76.0  -0.429
##  sound0 visualization2 - sound1 visualization3    -4.10 11.20 60.7  -0.365
##  sound1 visualization2 - sound0 visualization3    -3.10 11.20 60.7  -0.276
##  sound1 visualization2 - sound1 visualization3    -4.40  6.52 76.0  -0.675
##  sound0 visualization3 - sound1 visualization3    -1.30 11.20 60.7  -0.116
##  p.value
##   1.0000
##   1.0000
##   1.0000
##   0.9997
##   0.9998
##   1.0000
```

```
##   0.9992
##   1.0000
##   0.9996
##   1.0000
##   0.9981
##   0.9991
##   0.9998
##   0.9842
##   1.0000
##
## Degrees-of-freedom method: kenward-roger
## P value adjustment: tukey method for comparing a family of 6 estimates
##
## Analysis of Variance of Aligned Rank Transformed Data
##
## Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)
## Model: Mixed Effects (lmer)
## Response: art(Q3_10)
##
##                             F Df Df.res  Pr(>F)
## 1 sound               0.43457  1     38 0.51373
## 2 visualization       1.73507  2     76 0.18330
## 3 sound:visualization 1.03487  2     76 0.36023
## ---
## Signif. codes:   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## $emmeans
##  sound visualization emmean   SE   df lower.CL upper.CL
##  0     1               60.5 7.91 56.8     44.6     76.4
##  1     1               58.0 7.91 56.8     42.2     73.9
##  0     2               62.4 7.91 56.8     46.5     78.2
##  1     2               56.4 7.91 56.8     40.5     72.2
##  0     3               59.9 7.91 56.8     44.0     75.8
##  1     3               65.8 7.91 56.8     50.0     81.7
##
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
## $contrasts
##  contrast                                      estimate    SE   df t.ratio
##  sound0 visualization1 - sound1 visualization1     2.45 11.20 56.8   0.219
##  sound0 visualization1 - sound0 visualization2    -1.85  6.03 76.0  -0.307
##  sound0 visualization1 - sound1 visualization2     4.15 11.20 56.8   0.371
##  sound0 visualization1 - sound0 visualization3     0.60  6.03 76.0   0.099
##  sound0 visualization1 - sound1 visualization3    -5.35 11.20 56.8  -0.478
##  sound1 visualization1 - sound0 visualization2    -4.30 11.20 56.8  -0.384
##  sound1 visualization1 - sound1 visualization2     1.70  6.03 76.0   0.282
##  sound1 visualization1 - sound0 visualization3    -1.85 11.20 56.8  -0.165
##  sound1 visualization1 - sound1 visualization3    -7.80  6.03 76.0  -1.293
##  sound0 visualization2 - sound1 visualization2     6.00 11.20 56.8   0.536
##  sound0 visualization2 - sound0 visualization3     2.45  6.03 76.0   0.406
##  sound0 visualization2 - sound1 visualization3    -3.50 11.20 56.8  -0.313
##  sound1 visualization2 - sound0 visualization3    -3.55 11.20 56.8  -0.317
```

```
##  sound1 visualization2 - sound1 visualization3    -9.50  6.03 76.0  -1.575
##  sound0 visualization3 - sound1 visualization3    -5.95 11.20 56.8  -0.532
##  p.value
##   0.9999
##   0.9996
##   0.9990
##   1.0000
##   0.9968
##   0.9989
##   0.9998
##   1.0000
##   0.7880
##   0.9944
##   0.9985
##   0.9996
##   0.9995
##   0.6174
##   0.9946
##
## Degrees-of-freedom method: kenward-roger
## P value adjustment: tukey method for comparing a family of 6 estimates
##
## Analysis of Variance of Aligned Rank Transformed Data
##
## Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)
## Model: Mixed Effects (lmer)
## Response: art(Q3_11)
##
##                              F Df Df.res   Pr(>F)
## 1 sound               2.0467  1     38 0.160710
## 2 visualization       2.3623  2     76 0.101088
## 3 sound:visualization 4.8842  2     76 0.010104 *
## ---
## Signif. codes:   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## $emmeans
##  sound visualization emmean   SE df lower.CL upper.CL
##  0     1               60.4 7.86 52     44.6     76.2
##  1     1               59.0 7.86 52     43.2     74.7
##  0     2               64.3 7.86 52     48.6     80.1
##  1     2               55.0 7.86 52     39.3     70.8
##  0     3               55.2 7.86 52     39.5     71.0
##  1     3               69.0 7.86 52     53.2     84.8
##
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
## $contrasts
##  contrast                                      estimate   SE df t.ratio p.value
##  sound0 visualization1 - sound1 visualization1     1.45 11.1 52   0.130  1.0000
##  sound0 visualization1 - sound0 visualization2    -3.95  5.3 76  -0.745  0.9755
##  sound0 visualization1 - sound1 visualization2     5.35 11.1 52   0.481  0.9966
##  sound0 visualization1 - sound0 visualization3     5.15  5.3 76   0.971  0.9256
```

```
##  sound0 visualization1 - sound1 visualization3    -8.60 11.1 52  -0.773  0.9708
##  sound1 visualization1 - sound0 visualization2    -5.40 11.1 52  -0.486  0.9965
##  sound1 visualization1 - sound1 visualization2     3.90  5.3 76   0.736  0.9769
##  sound1 visualization1 - sound0 visualization3     3.70 11.1 52   0.333  0.9994
##  sound1 visualization1 - sound1 visualization3   -10.05  5.3 76  -1.895  0.4130
##  sound0 visualization2 - sound1 visualization2     9.30 11.1 52   0.836  0.9593
##  sound0 visualization2 - sound0 visualization3     9.10  5.3 76   1.716  0.5256
##  sound0 visualization2 - sound1 visualization3    -4.65 11.1 52  -0.418  0.9983
##  sound1 visualization2 - sound0 visualization3    -0.20 11.1 52  -0.018  1.0000
##  sound1 visualization2 - sound1 visualization3   -13.95  5.3 76  -2.631  0.1023
##  sound0 visualization3 - sound1 visualization3   -13.75 11.1 52  -1.236  0.8169
##
## Degrees-of-freedom method: kenward-roger
## P value adjustment: tukey method for comparing a family of 6 estimates
```

```
## # A tibble: 66 × 6
##    sound visualization question  mean    sd     n
##    <fct> <fct>         <chr>    <dbl> <dbl> <int>
##  1 0     Ray           Q3_1      78.2  22.8    20
##  2 0     Ray           Q3_10     77.8  24.8    20
##  3 0     Ray           Q3_11     82.2  23.1    20
##  4 0     Ray           Q3_2      79.6  20.1    20
##  5 0     Ray           Q3_3      81.3  19.8    20
##  6 0     Ray           Q3_4      87.2  14.5    20
##  7 0     Ray           Q3_5      85.8  17.0    20
##  8 0     Ray           Q3_6      81.4  23.3    20
##  9 0     Ray           Q3_7      79.2  23.4    20
## 10 0     Ray           Q3_8      76.0  28.9    20
## 11 0     Ray           Q3_9      74.6  28.1    20
## 12 0     Hover         Q3_1      81.0  16.4    20
## 13 0     Hover         Q3_10     77.0  18.2    20
## 14 0     Hover         Q3_11     84.8  16.9    20
## 15 0     Hover         Q3_2      80.2  19.6    20
## 16 0     Hover         Q3_3      74.6  22.3    20
## 17 0     Hover         Q3_4      81.6  16.2    20
## 18 0     Hover         Q3_5      81.9  18.0    20
## 19 0     Hover         Q3_6      76.0  26.8    20
## 20 0     Hover         Q3_7      74.5  25.6    20
## 21 0     Hover         Q3_8      75.0  26.2    20
## 22 0     Hover         Q3_9      75.6  27.3    20
## 23 0     Outline       Q3_1      74.4  25.0    20
## 24 0     Outline       Q3_10     73.2  28.8    20
## 25 0     Outline       Q3_11     78.9  26.4    20
## 26 0     Outline       Q3_2      72.2  29.3    20
## 27 0     Outline       Q3_3      70.8  31.4    20
## 28 0     Outline       Q3_4      72.4  30.0    20
## 29 0     Outline       Q3_5      71.8  27.7    20
## 30 0     Outline       Q3_6      71.7  30.5    20
## 31 0     Outline       Q3_7      71.1  26.7    20
## 32 0     Outline       Q3_8      72.6  26.7    20
## 33 0     Outline       Q3_9      72.1  28.8    20
## 34 1     Ray           Q3_1      73.6  12.5    20
## 35 1     Ray           Q3_10     74.3  20.5    20
## 36 1     Ray           Q3_11     75.4  20.2    20
## 37 1     Ray           Q3_2      71.6  18.9    20
## 38 1     Ray           Q3_3      72.5  20.0    20
## 39 1     Ray           Q3_4      74.2  17.0    20
## 40 1     Ray           Q3_5      73.2  16.7    20
## 41 1     Ray           Q3_6      71.2  20.8    20
## 42 1     Ray           Q3_7      70.8  18.7    20
## 43 1     Ray           Q3_8      61.0  27.8    20
## 44 1     Ray           Q3_9      59.4  29.4    20
## 45 1     Hover         Q3_1      67.8  21.7    20
## 46 1     Hover         Q3_10     67.8  25.1    20
## 47 1     Hover         Q3_11     70.0  24.7    20
## 48 1     Hover         Q3_2      65.2  19.1    20
## 49 1     Hover         Q3_3      62.7  23.6    20
```

```
## 50 1      Hover         Q3_4      66.2  27.0    20
## 51 1      Hover         Q3_5      65.8  25.8    20
## 52 1      Hover         Q3_6      63.6  25.3    20
## 53 1      Hover         Q3_7      61.2  25.4    20
## 54 1      Hover         Q3_8      63.3  25.6    20
## 55 1      Hover         Q3_9      63.4  25.7    20
## 56 1      Outline       Q3_1      73.1  24      20
## 57 1      Outline       Q3_10     76.1  23.5    20
## 58 1      Outline       Q3_11     79.6  24.0    20
## 59 1      Outline       Q3_2      74.2  24.4    20
## 60 1      Outline       Q3_3      73.8  23.9    20
## 61 1      Outline       Q3_4      73.2  26.9    20
## 62 1      Outline       Q3_5      69.7  30.0    20
## 63 1      Outline       Q3_6      69.3  28.4    20
## 64 1      Outline       Q3_7      71.2  22.8    20
## 65 1      Outline       Q3_8      62.2  30.4    20
## 66 1      Outline       Q3_9      61.3  30.1    20
```

```
## [1] "Demographics Summary..."
```

```
##
##  1  2
## 24 16
```

```
##
##  1  2
## 24 16
```

```
##
##  1  2
## 18 22
```

```
##
##  1
## 40
```

```
##
##  2  3
## 18 22
```

```
##        Q1              Q2           Q3              Q4_1          Q4_2     
##  Min.   : 1.00   Min.   :1.0   Min.   : 1.911   Min.   :1.0   Min.   :1.00  
##  1st Qu.:10.75   1st Qu.:1.0   1st Qu.:21.000   1st Qu.:1.0   1st Qu.:1.00  
##  Median :20.50   Median :1.0   Median :23.000   Median :1.0   Median :2.00  
##  Mean   :20.50   Mean   :1.4   Mean   :22.303   Mean   :1.4   Mean   :1.55  
##  3rd Qu.:30.25   3rd Qu.:2.0   3rd Qu.:24.000   3rd Qu.:2.0   3rd Qu.:2.00  
##  Max.   :40.00   Max.   :2.0   Max.   :26.000   Max.   :2.0   Max.   :2.00  
##  NA's   :2       NA's   :2                      NA's   :2     NA's   :2     
##        Q5          Q6      
##  Min.   :1   Min.   :2.00  
##  1st Qu.:1   1st Qu.:2.00  
##  Median :1   Median :3.00  
##  Mean   :1   Mean   :2.55  
##  3rd Qu.:1   3rd Qu.:3.00  
##  Max.   :1   Max.   :3.00  
##  NA's   :2   NA's   :2
```

```
## [1] 3.723255
```

```
## 
## Attaching package: 'reshape2'
```

```
## The following object is masked from 'package:tidyr':
## 
##     smiths
```

```
## Warning: package 'PMCMRplus' was built under R version 4.4.3
```

```
## [1] "PostStudy Summary..."
```

```
##   Q1 Q2_1 Q2_2 Q2_4
## 1  1    1    2    3
## 2  2    1    3    2
## 3  3    3    2    1
## 4  4    3    2    1
## 5  5    1    3    2
## 6  6    3    1    2
##                                                                                                 
Q3
## 1 I could constantly see my razor and my partners upuntill the last round, and the gaze hover 
was helpful
## 2                                                                      Constant ray allowed m
e to focus .
## 3                                  outline was more visually appealing and just as visible a
s the others
## 4                   The outline was clearer than the hover. And the constant ray wasn't alway
s necessary.
## 5                                                                                         eas
ier to focus
## 6                      it was easy to hover than seeing outline and ray is sometimes kind of 
out of focus
##   Q4_1 Q4_2 Q4_4
## 1    1    2    3
## 2    2    3    1
## 3    3    2    1
## 4    3    2    1
## 5    1    3    2
## 6    2    1    3
##                                                                                                 
Q5
## 1 The Ray helped keep track of my eye contact, the hover was able to focus on the particular 
item my eyes wanted to point and the outline made it easier
## 2                                                                                             
outline made the objects brighter and better to see.
## 3                                                                                             
outline made it easy to identify objects and looked better
## 4                                                                                     It was 
easier to see which item I picked up with the gaze outline.
## 5                                                                                             
i can see what i'm doing
## 6                                                                                             
##   Q7                                                     Q8
## 1  2                                  Did not observe that
## 2  2                                I did not notice them.
## 3  1                           helps me see what i pick up
## 4  1 I liked having the big outlines to make my selections clearer.
## 5  2                          didnt notice dangerous items
## 6  2
```

```
## [1] "Friedman Test Result for Q2 variables:"
```

```
##
##  Friedman rank sum test
##
## data:  Rank_Q2 and Condition_Q2 and Q1
## Friedman chi-squared = 6.65, df = 2, p-value = 0.03597
```

```
## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties
```

```
## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties
## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties
```

```
## [1] "Post-hoc Wilcoxon Signed-Rank Test Results for Q2 variables:"
##
##  Pairwise comparisons using Wilcoxon signed rank test with continuity correction
##
## data:  data_long_Q2$Rank_Q2 and data_long_Q2$Condition_Q2
##
##      Q2_1  Q2_2
## Q2_2 0.471 -
## Q2_4 0.727 0.033
##
## P value adjustment method: bonferroni
```

```
## [1] "Friedman Test Result for Q4 variables:"
```

```
##
##  Friedman rank sum test
##
## data:  Rank_Q4 and Condition_Q4 and Q1
## Friedman chi-squared = 8.15, df = 2, p-value = 0.01699
```

```
## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties
## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties
## Warning in wilcox.test.default(xi, xj, paired = paired, ...): cannot compute
## exact p-value with ties
```

```
## [1] "Post-hoc Wilcoxon Signed-Rank Test Results for Q4 variables:"
##
##  Pairwise comparisons using Wilcoxon signed rank test with continuity correction
##
## data:  data_long_Q4$Rank_Q4 and data_long_Q4$Condition_Q4
##
##      Q4_1 Q4_2
## Q4_2 1.00 -
## Q4_4 0.18 0.03
##
## P value adjustment method: bonferroni
```

```
## [1] "Visual cue distribution (Q7):"
##
##  1  2
## 21 19
```

```
## [1] "Summary of the post study data:"
```

```
##        Q1             Q2_1            Q2_2          Q2_4
##  Min.   : 1.00   Min.   :1.000   Min.   :1.0   Min.   :1.000
##  1st Qu.:10.75   1st Qu.:1.000   1st Qu.:2.0   1st Qu.:1.000
##  Median :20.50   Median :2.000   Median :2.5   Median :2.000
##  Mean   :20.50   Mean   :1.975   Mean   :2.3   Mean   :1.725
##  3rd Qu.:30.25   3rd Qu.:3.000   3rd Qu.:3.0   3rd Qu.:2.000
##  Max.   :40.00   Max.   :3.000   Max.   :3.0   Max.   :3.000
##       Q3                 Q4_1            Q4_2            Q4_4
##  Length:40          Min.   :1.000   Min.   :1.000   Min.   :1.00
##  Class :character   1st Qu.:1.750   1st Qu.:2.000   1st Qu.:1.00
##  Mode  :character   Median :2.000   Median :2.000   Median :1.00
##                     Mean   :2.075   Mean   :2.275   Mean   :1.65
##                     3rd Qu.:3.000   3rd Qu.:3.000   3rd Qu.:2.00
##                     Max.   :3.000   Max.   :3.000   Max.   :3.00
##       Q5                  Q7             Q8
##  Length:40          Min.   :1.000   Length:40
##  Class :character   1st Qu.:1.000   Class :character
##  Mode  :character   Median :1.000   Mode  :character
##                     Mean   :1.475
##                     3rd Qu.:2.000
##                     Max.   :2.000
```

```
## ── Attaching core tidyverse packages ──────────────────────── tidyverse 2.0.0 ──
## ✓ forcats   1.0.0     ✓ purrr     1.0.2
## ✓ ggplot2   3.5.1     ✓ readr     2.1.5
## ✓ lubridate 1.9.3     ✓ stringr   1.5.1
## ── Conflicts ────────────────────────────────────────── tidyverse_conflicts() ──
## ✗ dplyr::filter() masks stats::filter()
## ✗ dplyr::lag()    masks stats::lag()
## ℹ Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to becom
e errors
```

```
##
## ANOVA: eye_contact_instances
```

```
## Analysis of Variance of Aligned Rank Transformed Data
##
## Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)
## Model: Mixed Effects (lmer)
## Response: art(eye_contact_instances)
##
##                          F Df Df.res  Pr(>F)
## 1 sound           0.18757  1     18 0.67010
## 2 condition       1.06282  2     36 0.35607
## 3 sound:condition 1.85555  2     36 0.17101
## ---
## Signif. codes:   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## ANOVA: total_eye_contact_time
```

```
## Analysis of Variance of Aligned Rank Transformed Data
##
## Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)
## Model: Mixed Effects (lmer)
## Response: art(total_eye_contact_time)
##
##                         F Df Df.res   Pr(>F)
## 1 sound           0.7586  1     18 0.395236
## 2 condition       1.5480  2     36 0.226488
## 3 sound:condition 5.0567  2     36 0.011603 *
## ---
## Signif. codes:   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## ANOVA: Total Shared Focus
```

```
## Analysis of Variance of Aligned Rank Transformed Data
##
## Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)
## Model: Mixed Effects (lmer)
## Response: art(total_shared_focus)
##
##                        F Df Df.res  Pr(>F)
## 1 sound           1.3706  1     18 0.25697
## 2 condition       1.3011  2     36 0.28474
## 3 sound:condition 1.1837  2     36 0.31778
## ---
## Signif. codes:   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## ANOVA: Focus Instances
```

```
## boundary (singular) fit: see help('isSingular')
```

```
## Analysis of Variance of Aligned Rank Transformed Data
##
## Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)
## Model: Mixed Effects (lmer)
## Response: art(focus_instances)
##
##                         F Df Df.res   Pr(>F)
## 1 sound           1.08119  1     18 0.312197
## 2 condition       4.63921  2     36 0.016121 *
## 3 sound:condition 0.96252  2     36 0.391539
## ---
## Signif. codes:   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## ANOVA: Individual Rotation_Parent Time
```

```
## Analysis of Variance of Aligned Rank Transformed Data
##
## Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)
## Model: Mixed Effects (lmer)
## Response: art(individual_rotation_parent_time)
##
##                         F Df Df.res   Pr(>F)
## 1 sound           4.27994  1     18 0.053238 .
## 2 condition       0.73246  2     36 0.487753
## 3 sound:condition 0.76435  2     36 0.473045
## ---
## Signif. codes:   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## ANOVA: Individual Rotation_Parent Count
```

```
## Analysis of Variance of Aligned Rank Transformed Data
##
## Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)
## Model: Mixed Effects (lmer)
## Response: art(individual_rotation_parent_count)
##
##                         F Df Df.res  Pr(>F)
## 1 sound           2.84511  1     18 0.10891
## 2 condition       0.97039  2     36 0.38863
## 3 sound:condition 0.86050  2     36 0.43147
## ---
## Signif. codes:   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Post-hoc: Eye Contact Instances
```

```
## $emmeans
##  sound condition emmean   SE   df lower.CL upper.CL
##  0     1           40.5 5.17 53.4    30.12     50.9
##  1     1           35.9 5.17 53.4    25.52     46.3
##  0     2           27.1 5.17 53.4    16.72     37.5
##  1     2           32.1 5.17 53.4    21.72     42.5
##  0     3           30.8 5.17 53.4    20.42     41.2
##  1     3           16.6 5.17 53.4     6.22     27.0
## 
## Degrees-of-freedom method: kenward-roger 
## Confidence level used: 0.95 
## 
## $contrasts
##  contrast                              estimate   SE   df t.ratio p.value
##  sound0 condition1 - sound1 condition1      4.6 7.32 53.4   0.629  0.9884
##  sound0 condition1 - sound0 condition2     13.4 7.05 36.0   1.901  0.4178
##  sound0 condition1 - sound1 condition2      8.4 7.32 53.4   1.148  0.8589
##  sound0 condition1 - sound0 condition3      9.7 7.05 36.0   1.376  0.7405
##  sound0 condition1 - sound1 condition3     23.9 7.32 53.4   3.266  0.0223
##  sound1 condition1 - sound0 condition2      8.8 7.32 53.4   1.203  0.8337
##  sound1 condition1 - sound1 condition2      3.8 7.05 36.0   0.539  0.9941
##  sound1 condition1 - sound0 condition3      5.1 7.32 53.4   0.697  0.9815
##  sound1 condition1 - sound1 condition3     19.3 7.05 36.0   2.739  0.0921
##  sound0 condition2 - sound1 condition2     -5.0 7.32 53.4  -0.683  0.9831
##  sound0 condition2 - sound0 condition3     -3.7 7.05 36.0  -0.525  0.9948
##  sound0 condition2 - sound1 condition3     10.5 7.32 53.4   1.435  0.7059
##  sound1 condition2 - sound0 condition3      1.3 7.32 53.4   0.178  1.0000
##  sound1 condition2 - sound1 condition3     15.5 7.05 36.0   2.199  0.2630
##  sound0 condition3 - sound1 condition3     14.2 7.32 53.4   1.940  0.3897
## 
## Degrees-of-freedom method: kenward-roger 
## P value adjustment: tukey method for comparing a family of 6 estimates
```

```
## 
## Post-hoc: Total Eye Contact Time
```

```
## $emmeans
##  sound condition emmean   SE   df lower.CL upper.CL
##  0     1           30.4 4.83 53.9    20.72     40.1
##  1     1           42.6 4.83 53.9    32.92     52.3
##  0     2           23.8 4.83 53.9    14.12     33.5
##  1     2           42.1 4.83 53.9    32.42     51.8
##  0     3           27.3 4.83 53.9    17.62     37.0
##  1     3           16.8 4.83 53.9     7.12     26.5
##
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
## $contrasts
##  contrast                              estimate   SE   df t.ratio p.value
##  sound0 condition1 - sound1 condition1    -12.2 6.83 53.9  -1.786  0.4831
##  sound0 condition1 - sound0 condition2      6.6 6.75 36.0   0.978  0.9220
##  sound0 condition1 - sound1 condition2    -11.7 6.83 53.9  -1.713  0.5295
##  sound0 condition1 - sound0 condition3      3.1 6.75 36.0   0.459  0.9972
##  sound0 condition1 - sound1 condition3     13.6 6.83 53.9   1.991  0.3608
##  sound1 condition1 - sound0 condition2     18.8 6.83 53.9   2.752  0.0814
##  sound1 condition1 - sound1 condition2      0.5 6.75 36.0   0.074  1.0000
##  sound1 condition1 - sound0 condition3     15.3 6.83 53.9   2.240  0.2370
##  sound1 condition1 - sound1 condition3     25.8 6.75 36.0   3.823  0.0062
##  sound0 condition2 - sound1 condition2    -18.3 6.83 53.9  -2.679  0.0963
##  sound0 condition2 - sound0 condition3     -3.5 6.75 36.0  -0.519  0.9951
##  sound0 condition2 - sound1 condition3      7.0 6.83 53.9   1.025  0.9076
##  sound1 condition2 - sound0 condition3     14.8 6.83 53.9   2.167  0.2701
##  sound1 condition2 - sound1 condition3     25.3 6.75 36.0   3.749  0.0076
##  sound0 condition3 - sound1 condition3     10.5 6.83 53.9   1.537  0.6422
##
## Degrees-of-freedom method: kenward-roger
## P value adjustment: tukey method for comparing a family of 6 estimates
```

```
##
## Post-hoc: Total Shared Focus
```

```
## $emmeans
##  sound condition emmean   SE df lower.CL upper.CL
##  0     1           27.2 5.63 52     15.9     38.5
##  1     1           32.0 5.63 52     20.7     43.3
##  0     2           25.2 5.63 52     13.9     36.5
##  1     2           36.6 5.63 52     25.3     47.9
##  0     3           33.3 5.63 52     22.0     44.6
##  1     3           28.7 5.63 52     17.4     40.0
## 
## Degrees-of-freedom method: kenward-roger 
## Confidence level used: 0.95 
## 
## $contrasts
##  contrast                              estimate   SE df t.ratio p.value
##  sound0 condition1 - sound1 condition1     -4.8 7.96 52  -0.603  0.9904
##  sound0 condition1 - sound0 condition2      2.0 7.39 36   0.271  0.9998
##  sound0 condition1 - sound1 condition2     -9.4 7.96 52  -1.181  0.8437
##  sound0 condition1 - sound0 condition3     -6.1 7.39 36  -0.825  0.9608
##  sound0 condition1 - sound1 condition3     -1.5 7.96 52  -0.188  1.0000
##  sound1 condition1 - sound0 condition2      6.8 7.96 52   0.854  0.9554
##  sound1 condition1 - sound1 condition2     -4.6 7.39 36  -0.622  0.9886
##  sound1 condition1 - sound0 condition3     -1.3 7.96 52  -0.163  1.0000
##  sound1 condition1 - sound1 condition3      3.3 7.39 36   0.447  0.9976
##  sound0 condition2 - sound1 condition2    -11.4 7.96 52  -1.432  0.7074
##  sound0 condition2 - sound0 condition3     -8.1 7.39 36  -1.096  0.8798
##  sound0 condition2 - sound1 condition3     -3.5 7.96 52  -0.440  0.9978
##  sound1 condition2 - sound0 condition3      3.3 7.96 52   0.415  0.9983
##  sound1 condition2 - sound1 condition3      7.9 7.39 36   1.069  0.8904
##  sound0 condition3 - sound1 condition3      4.6 7.96 52   0.578  0.9921
## 
## Degrees-of-freedom method: kenward-roger 
## P value adjustment: tukey method for comparing a family of 6 estimates
```

```
## 
## Post-hoc: Focus Instances
```

```
## $emmeans
##  sound condition emmean   SE df lower.CL upper.CL
##  0     1           31.0 5.66 54     19.6     42.4
##  1     1           31.9 5.66 54     20.5     43.3
##  0     2           26.6 5.66 54     15.2     38.0
##  1     2           34.8 5.66 54     23.4     46.2
##  0     3           33.1 5.66 54     21.7     44.5
##  1     3           25.6 5.66 54     14.2     37.0
## 
## Degrees-of-freedom method: kenward-roger 
## Confidence level used: 0.95 
## 
## $contrasts
##  contrast                              estimate   SE df t.ratio p.value
##  sound0 condition1 - sound1 condition1     -0.9 8.01 54  -0.112  1.0000
##  sound0 condition1 - sound0 condition2      4.4 8.01 36   0.549  0.9936
##  sound0 condition1 - sound1 condition2     -3.8 8.01 54  -0.474  0.9969
##  sound0 condition1 - sound0 condition3     -2.1 8.01 36  -0.262  0.9998
##  sound0 condition1 - sound1 condition3      5.4 8.01 54   0.674  0.9841
##  sound1 condition1 - sound0 condition2      5.3 8.01 54   0.662  0.9853
##  sound1 condition1 - sound1 condition2     -2.9 8.01 36  -0.362  0.9991
##  sound1 condition1 - sound0 condition3     -1.2 8.01 54  -0.150  1.0000
##  sound1 condition1 - sound1 condition3      6.3 8.01 36   0.787  0.9680
##  sound0 condition2 - sound1 condition2     -8.2 8.01 54  -1.024  0.9079
##  sound0 condition2 - sound0 condition3     -6.5 8.01 36  -0.812  0.9635
##  sound0 condition2 - sound1 condition3      1.0 8.01 54   0.125  1.0000
##  sound1 condition2 - sound0 condition3      1.7 8.01 54   0.212  0.9999
##  sound1 condition2 - sound1 condition3      9.2 8.01 36   1.149  0.8574
##  sound0 condition3 - sound1 condition3      7.5 8.01 54   0.936  0.9352
## 
## Degrees-of-freedom method: kenward-roger 
## P value adjustment: tukey method for comparing a family of 6 estimates
```

```
## 
## Post-hoc: Individual Rotation_Parent Time
```

```
## $emmeans
##  sound condition emmean   SE   df lower.CL upper.CL
##  0     1           28.4 5.64 51.9     17.1     39.7
##  1     1           31.1 5.64 51.9     19.8     42.4
##  0     2           29.4 5.64 51.9     18.1     40.7
##  1     2           37.9 5.64 51.9     26.6     49.2
##  0     3           30.3 5.64 51.9     19.0     41.6
##  1     3           25.9 5.64 51.9     14.6     37.2
##
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
## $contrasts
##  contrast                              estimate   SE   df t.ratio p.value
##  sound0 condition1 - sound1 condition1     -2.7 7.98 51.9  -0.339  0.9994
##  sound0 condition1 - sound0 condition2     -1.0 7.39 36.0  -0.135  1.0000
##  sound0 condition1 - sound1 condition2     -9.5 7.98 51.9  -1.191  0.8391
##  sound0 condition1 - sound0 condition3     -1.9 7.39 36.0  -0.257  0.9998
##  sound0 condition1 - sound1 condition3      2.5 7.98 51.9   0.313  0.9996
##  sound1 condition1 - sound0 condition2      1.7 7.98 51.9   0.213  0.9999
##  sound1 condition1 - sound1 condition2     -6.8 7.39 36.0  -0.920  0.9387
##  sound1 condition1 - sound0 condition3      0.8 7.98 51.9   0.100  1.0000
##  sound1 condition1 - sound1 condition3      5.2 7.39 36.0   0.704  0.9803
##  sound0 condition2 - sound1 condition2     -8.5 7.98 51.9  -1.066  0.8926
##  sound0 condition2 - sound0 condition3     -0.9 7.39 36.0  -0.122  1.0000
##  sound0 condition2 - sound1 condition3      3.5 7.98 51.9   0.439  0.9978
##  sound1 condition2 - sound0 condition3      7.6 7.98 51.9   0.953  0.9304
##  sound1 condition2 - sound1 condition3     12.0 7.39 36.0   1.624  0.5888
##  sound0 condition3 - sound1 condition3      4.4 7.98 51.9   0.552  0.9936
##
## Degrees-of-freedom method: kenward-roger
## P value adjustment: tukey method for comparing a family of 6 estimates
```

```
##
## Post-hoc: Individual Rotation_Parent Count
```

```
## $emmeans
##  sound condition emmean   SE   df lower.CL upper.CL
##  0     1           30.9 5.64 53.8     19.6     42.2
##  1     1           31.5 5.64 53.8     20.2     42.8
##  0     2           26.8 5.64 53.8     15.4     38.1
##  1     2           37.4 5.64 53.8     26.1     48.7
##  0     3           29.9 5.64 53.8     18.6     41.3
##  1     3           26.5 5.64 53.8     15.2     37.8
##
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
## $contrasts
##  contrast                              estimate   SE   df t.ratio p.value
##  sound0 condition1 - sound1 condition1    -0.60 7.98 53.8  -0.075  1.0000
##  sound0 condition1 - sound0 condition2     4.15 7.83 36.0   0.530  0.9946
##  sound0 condition1 - sound1 condition2    -6.50 7.98 53.8  -0.815  0.9636
##  sound0 condition1 - sound0 condition3     0.95 7.83 36.0   0.121  1.0000
##  sound0 condition1 - sound1 condition3     4.40 7.98 53.8   0.551  0.9936
##  sound1 condition1 - sound0 condition2     4.75 7.98 53.8   0.595  0.9909
##  sound1 condition1 - sound1 condition2    -5.90 7.83 36.0  -0.754  0.9734
##  sound1 condition1 - sound0 condition3     1.55 7.98 53.8   0.194  1.0000
##  sound1 condition1 - sound1 condition3     5.00 7.83 36.0   0.639  0.9872
##  sound0 condition2 - sound1 condition2   -10.65 7.98 53.8  -1.335  0.7646
##  sound0 condition2 - sound0 condition3    -3.20 7.83 36.0  -0.409  0.9984
##  sound0 condition2 - sound1 condition3     0.25 7.98 53.8   0.031  1.0000
##  sound1 condition2 - sound0 condition3     7.45 7.98 53.8   0.934  0.9360
##  sound1 condition2 - sound1 condition3    10.90 7.83 36.0   1.393  0.7309
##  sound0 condition3 - sound1 condition3     3.45 7.98 53.8   0.432  0.9980
##
## Degrees-of-freedom method: kenward-roger
## P value adjustment: tukey method for comparing a family of 6 estimates
```

```
##
## ANOVA: num_danger_obj
```

```
## Analysis of Variance of Aligned Rank Transformed Data
##
## Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)
## Model: Mixed Effects (lmer)
## Response: art(num_danger_obj)
##
##                          F Df Df.res  Pr(>F)
## 1 sound           0.69522  1     18 0.41532
## 2 condition       0.86297  2     36 0.43045
## 3 sound:condition 1.14227  2     36 0.33039
## ---
## Signif. codes:   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Post-hoc: Danger Object
```

```
## $emmeans
##  sound condition emmean   SE   df lower.CL upper.CL
##  0     1           32.3 5.59 30.8     20.9     43.7
##  1     1           32.5 5.59 30.8     21.1     43.9
##  0     2           24.4 5.59 30.8     13.0     35.8
##  1     2           29.7 5.59 30.8     18.3     41.1
##  0     3           26.7 5.59 30.8     15.3     38.1
##  1     3           37.4 5.59 30.8     26.0     48.8
##
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
## $contrasts
##  contrast                              estimate   SE   df t.ratio p.value
##  sound0 condition1 - sound1 condition1     -0.2 7.90 30.8  -0.025  1.0000
##  sound0 condition1 - sound0 condition2      7.9 4.91 36.0   1.608  0.5988
##  sound0 condition1 - sound1 condition2      2.6 7.90 30.8   0.329  0.9994
##  sound0 condition1 - sound0 condition3      5.6 4.91 36.0   1.140  0.8614
##  sound0 condition1 - sound1 condition3     -5.1 7.90 30.8  -0.645  0.9864
##  sound1 condition1 - sound0 condition2      8.1 7.90 30.8   1.025  0.9059
##  sound1 condition1 - sound1 condition2      2.8 4.91 36.0   0.570  0.9924
##  sound1 condition1 - sound0 condition3      5.8 7.90 30.8   0.734  0.9761
##  sound1 condition1 - sound1 condition3     -4.9 4.91 36.0  -0.997  0.9158
##  sound0 condition2 - sound1 condition2     -5.3 7.90 30.8  -0.671  0.9839
##  sound0 condition2 - sound0 condition3     -2.3 4.91 36.0  -0.468  0.9970
##  sound0 condition2 - sound1 condition3    -13.0 7.90 30.8  -1.645  0.5764
##  sound1 condition2 - sound0 condition3      3.0 7.90 30.8   0.380  0.9989
##  sound1 condition2 - sound1 condition3     -7.7 4.91 36.0  -1.567  0.6245
##  sound0 condition3 - sound1 condition3    -10.7 7.90 30.8  -1.354  0.7530
##
## Degrees-of-freedom method: kenward-roger
## P value adjustment: tukey method for comparing a family of 6 estimates
```

```
##
## ANOVA: num_sorted_objects
```

```
## Analysis of Variance of Aligned Rank Transformed Data
##
## Table Type: Analysis of Deviance Table (Type III Wald F tests with Kenward-Roger df)
## Model: Mixed Effects (lmer)
## Response: art(num_sorted_objects)
##
##                          F Df Df.res  Pr(>F)
## 1 sound           0.69937  1     18 0.41396
## 2 condition       2.12079  2     36 0.13468
## 3 sound:condition 0.14619  2     36 0.86450
## ---
## Signif. codes:   0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Post-hoc: Sorted Objects
```

```
## $emmeans
##  sound condition emmean   SE   df lower.CL upper.CL
##  0     1           31.6 5.76 33.4     19.9     43.3
##  1     1           31.7 5.76 33.4     20.0     43.4
##  0     2           28.6 5.76 33.4     16.9     40.3
##  1     2           30.2 5.76 33.4     18.5     41.9
##  0     3           31.7 5.76 33.4     20.0     43.4
##  1     3           29.2 5.76 33.4     17.5     40.9
##
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
## $contrasts
##  contrast                              estimate   SE   df t.ratio p.value
##  sound0 condition1 - sound1 condition1     -0.1 8.14 33.4  -0.012  1.0000
##  sound0 condition1 - sound0 condition2      3.0 5.43 36.0   0.553  0.9934
##  sound0 condition1 - sound1 condition2      1.4 8.14 33.4   0.172  1.0000
##  sound0 condition1 - sound0 condition3     -0.1 5.43 36.0  -0.018  1.0000
##  sound0 condition1 - sound1 condition3      2.4 8.14 33.4   0.295  0.9997
##  sound1 condition1 - sound0 condition2      3.1 8.14 33.4   0.381  0.9989
##  sound1 condition1 - sound1 condition2      1.5 5.43 36.0   0.276  0.9998
##  sound1 condition1 - sound0 condition3      0.0 8.14 33.4   0.000  1.0000
##  sound1 condition1 - sound1 condition3      2.5 5.43 36.0   0.461  0.9972
##  sound0 condition2 - sound1 condition2     -1.6 8.14 33.4  -0.197  1.0000
##  sound0 condition2 - sound0 condition3     -3.1 5.43 36.0  -0.571  0.9923
##  sound0 condition2 - sound1 condition3     -0.6 8.14 33.4  -0.074  1.0000
##  sound1 condition2 - sound0 condition3     -1.5 8.14 33.4  -0.184  1.0000
##  sound1 condition2 - sound1 condition3      1.0 5.43 36.0   0.184  1.0000
##  sound0 condition3 - sound1 condition3      2.5 8.14 33.4   0.307  0.9996
##
## Degrees-of-freedom method: kenward-roger
## P value adjustment: tukey method for comparing a family of 6 estimates
```

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BIOGRAPHICAL SKETCH

Daniel Alexander Delgado is a McKnight Doctoral Fellow who received his Ph.D. in Computer Science from the University of Florida in 2025. His research spanned a broad range of topics, including privacy and security, human-machine interfaces, affective computing, collaborative augmented reality, task guidance, and applied eye-tracking. During his Ph.D. studies, Daniel mentored undergraduate students and led multiple research projects. He also earned a Master of Science in Computer Science en route to completing his doctorate.

Before pursuing his Ph.D., Daniel earned a Bachelor of Science in Computer Engineering from Florida State University, where he conducted undergraduate research in electrolytic battery cell synthesis and was a member of Alpha Chi Sigma, a professional fraternity specializing in the chemical sciences.

Following his Ph.D., Daniel will pursue a career in academia, where he will continue to push the boundaries of science.