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Transparency and Communication Patterns in Human-Robot Teaming

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TRANSPARENCY AND COMMUNICATION PATTERNS IN HUMAN-ROBOT TEAMING

by

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ABSTRACT

In anticipation of the complex, dynamic battlefields of the future, military operations are increasingly demanding robots with increased autonomous capabilities to support soldiers. Effective communication is necessary to establish a common ground on which human-robot teamwork can be established across the continuum of military operations. However, the types and format of communication for mixed-initiative collaboration is still not fully understood. This study explores two approaches to communication in human-robot interaction, transparency and communication pattern, and examines how manipulating these elements with a robot teammate affects its human counterpart in a collaborative exercise. Participants were coupled with a computer-simulated robot to perform a cordon-and-search-like task. A human-robot interface provided different transparency types—about the robot's decision making process alone, or about the robot's decision making process and its prediction of the human teammate's decision making process—and different communication patterns—either conveying information to the participant or both conveying information to and soliciting information from the participant. This experiment revealed that participants found robots that both conveyed and solicited information to be more animate, likeable, and intelligent than their less interactive counterparts, but working with those robots led to more misses in a target classification task. Furthermore, the act of responding to the robot led to a reduction in the number of correct identifications made, but only when the robot was solely providing information about its own decision making process. Findings from this effort inform the design of next-generation visual displays supporting human-robot teaming.

Dedicated to my family, mentors, cohorts, and friends who made me who I am today.

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LIST OF ACRONYMS

HRI	Human-Robot Interaction
ITC	Interactive Team Cognition
MMI	Multimodal Interface
POV	Point of View
SA	Situation Awareness
SAT	Situation Awareness-based Agent Transparency
UE4	Unreal Engine 4
U.S.	United States

CHAPTER ONE: INTRODUCTION

As automated systems become more complex, it becomes increasingly difficult for humans to understand the reasoning that leads these systems to their output (Chen & Barnes, 2014). To ameliorate this issue, transparency has been examined as a way to make the system "visible," allowing humans to establish accurate mental models of the system's actions (Chen et al., 2014; Karsenty & Botherel, 2005; Lyons, 2013; Maass, 1983). The need for this visibility grows as existing technology starts attempting to meet the desire for systems with greater intelligence and more autonomous capabilities; consequently, the approach to working with these more complex systems—autonomous systems with their own mental models— more closely resembles human teamwork rather than merely tool usage (Bradshaw, Hoffman, Woods, & Johnson, 2013; Defense Science Board, 2016; Ososky, Schuster, Phillips, & Jentsch, 2013). This paradigm shift towards more agentic systems necessitates a change in the way we examine the informational needs of humans and systems conducting shared tasks (Chen et al., 2018; Johnson et al., 2014).

Like other forms of automation, agents are machine or computer systems to which tasks are delegated, but unlike other forms of automation, agents can proactively pursue a set of goals and change its actions in response to its environment (Wooldridge & Jennings, 1995; Zhu & Hou, 2009). Not only do humans working with these agents have to establish accurate mental models of these systems, as machines, but they also have to understand the rationale driving the actions of those machines (Chen et al., 2014; Phillips, Ososky, Grove, & Jentsch, 2011). In the context of human-agent interaction, transparency has been described as a method by which a human and an agent can gain shared awareness, while maintaining their respective abilities to make autonomous decisions (Lyons, 2013). A transparent system facilitates this understanding by explaining its choices and behaviors, allowing its human operators to understand the way it works (Cramer et al., 2008).

Transparency is particularly important when agents are used in dynamic, complex environments where time-critical decision making is needed (Chen et al., 2018; Defense Science Board, 2016; Lakhmani, Abich, Barber, & Chen, 2016). Soldiers are frequently in these environments and thus the U.S. Military has invested resources into exploring the interaction between humans and agents (Chen & Barnes, 2014; Defense Science Board, 2016; U.S. Army, 2017). The U.S. military is actively pursuing strategies where robots, physically embodied agents, are teamed with soldiers to improve their overall combat effectiveness, though virtual agents and decision aides are also used in military contexts (Chen et al., 2018; Defense Science Board, 2016; Teo & Reinerman-Jones, 2014; U.S. Army, 2017). In order to meet the challenges of an evolving global state of affairs, the military has set a number of goals to guide the development and use of robots in the field (Defense Science Board, 2016; U.S. Army, 2017). One of these goals is to increase situational awareness in the field (Sycara & Sukthankar, 2006; U.S. Army, 2017). Given that robots can go places where soldiers cannot, they can gather information that is unique, yet complementary to information gathered by soldiers (Schuster, 2013; U.S. Army, 2017). This information can be used to support the mission goals and provide advantages to the team, such as increased survivability and more time to react (U.S. Army, 2017). In order to gain these benefits, however, human teammates must have a clear and accurate understanding of how the robot gathers information, processes that information, and makes decisions (Phillips et al., 2011). Not only must this information be available, but it must be shared in a way that is accessible to humans (Sycara & Sukthankar, 2006). A common cognitive framework can facilitate effective team communication, so robots with mentalistic architectures can more easily translate their decision making process (Chen & Barnes, 2014; Fan & Yen, 2004).

The Situation Awareness-based Agent Transparency (SAT) model applies psychological principles of situation awareness to robots' cognitive architecture, creating a framework for understanding the information needed to facilitate transparency in human-robot collaboration (Chen et al., 2014). By defining the kind of information needed to support transparent interaction, the SAT model allows designers to quantify and therefore assess a system's transparency (Chen et al., 2018; Chen et al., 2014). A more transparent system supports its operators' comprehension by providing them with information about its decision making process, while a less transparent system omits this information (Chen et al., 2014; Helldin, Falkman, Riveiro, Dahlbom, & Lebram, 2013; Miller, 2014). With the advancement of robots' capabilities in the military domain, however, a transparency paradigm focused on operator comprehension and the flow of information to the human may not be sufficient (Chen et al., 2018; Ososky, Sanders, Jentsch, Hancock, & Chen, 2014). More intelligent, autonomous robots can assume more responsibilities, to the extent that they can be thought of as collaborating team members rather than mere tools (Allen, Guinn, & Horvtz, 1999; Ososky et al., 2014). Unlike tools, synthetic collaborators act interdependently with their human counterparts, which necessitates not only a shared awareness with them, but also mutual feedback to maintain this awareness (Bradshaw et al., 2009; Bradshaw, Feltovich, & Johnson, 2012). This awareness, in human-human teams, is comprised of information pertaining to both the tasks at hand and the team members interacting to complete that task (Cannon-Bowers, Salas, & Converse, 1993; Mathieu, Heffner, Goodwin, Salas, & Cannon-Bowers, 2000; Sycara & Sukthankar, 2006). In human-robot teams, supporting mutual transparency—rather than agent transparency alone—should provide awareness of both the task and the team that synthetic and human team members should need to effectively collaborate (Chen et al., 2018; Johnson et al., 2012; Sycara & Sukthankar, 2006).

A common cognitive framework and relevant information is a prerequisite for transparent human-robot interaction (HRI), however, that interaction does not necessarily mimic human interaction (Chen & Barnes, 2014). Recent research into military HRI has advocated for bidirectional communication between human and robot team members (Barnes, Chen, & Hill, 2017; Shively et al., 2017). Under this communication paradigm, humans and robots can interact by individually or simultaneously projecting a message that their teammates can interpret; robots can both give and receive information, but this interaction does not necessitate a continuous, circular transaction of information between teammates (Barber et al., 2015; Barnlund, 1970; Héder, 2014; Marko, 1973; Schaefer, Straub, Chen, Putney, & Evans, 2017). Communication in human teams presupposes a reciprocal exchange of ideas, creating a shared understanding amongst teammates (Cooke, Gorman, Myers, & Duran, 2013; Salas, Shuffler, Thayer, Bedwell, & Lazzara, 2015). Establishing conventions for information transactions between humans and robots may bridge gaps between human-human and human-robot communication. The proposed study will investigate the informational requirements of human collaborators in a human-robot team and how that information can be communicated.

CHAPTER TWO: REVIEW OF THE LITERATURE

Agents

Automation can be defined as the delegation of tasks to a hardware or software system (Kisner & Raju, 1984; Zhu & Hou, 2009). These delegated tasks can be either physical or mental (Parasuraman, Sheridan, & Wickens, 2000). In order to delegate complex tasks, the system must be complex enough to actually complete these tasks. The field of artificial intelligence, in particular, has made great contributions to the development and study of these complex software systems (Jennings, Sycara, & Wooldridge, 1998; Russell & Norvig, 2009). When these systems are set up so that they can act to achieve the best expected outcome, then these systems can be described as a kind of agent (Jennings et al., 1998; Russell & Norvig, 2009).

In general, an agent is defined as something that acts, but in the context of automation and artificial intelligence, an agent is a hardware- or software-based system that perceives its environment and performs actions (Fan & Yen, 2004; Jennings et al., 1998; Russell & Norvig, 2009). While there are a number of different kinds of agents (e.g. intelligent, software, robotic), they all tend to be characterized by autonomy, proactivity, and reactivity (Fan & Yen, 2004; Franklin & Graesser, 1996; Russell & Norvig, 2009; Wooldridge & Jennings, 1995). Autonomy denotes that the agent is capable of functioning independently—without either direct intervention or relying on the knowledge of their designer—for a significant length of time (Russell & Norvig, 2009; Sycara & Sukthankar, 2006; Wooldridge & Jennings, 1995). Proactivity refers to the agent's ability to act in anticipation of future events in pursuit of a goal (Sycara & Sukthankar, 2006; Wooldridge & Jennings, 1995). Reactivity—also known as situatedness—

describes an agent's ability to receive input from its environment and respond in a timely fashion to changes within the environment (Jennings et al., 1998; Wooldridge & Jennings, 1995).

Agents, automated systems with autonomous capabilities, are being leveraged in a number of different fields—such as medicine, extractive industries, and the credit card industries (Defense Science Board, 2016). The U.S. military is not only leveraging agents, but actively pursuing agent technology and human-agent collaboration strategies in order to accomplish operational goals and maximize soldier safety (Defense Science Board, 2016; U.S. Army, 2017). One of the reasons why the U.S. military is allocating so many resources towards the development of agent technology is due to the third offset strategy (Eaglen, 2016; Work, 2015). Over the years, the U.S. military has pursued strategies to counteract—or offset—the great conventional forces of adversarial nations (Work, 2015). In the 1950s, Eisenhower's New Look Strategy, the first offset strategy, had the U.S. reduce military manpower and instead leverage its nuclear arsenal for deterrence (Work, 2015). In the 1970s and 1980s, when Soviet nuclear forces grew large enough that the U.S. nuclear arsenal was no longer an effective deterrent, the second offset strategy was developed—the development and use of light area sensor cueing aircraft that could accurately deliver conventional munitions in a way that would achieve the same destructive ends as tactical nuclear weapons (Work, 2015). With the advent of the new geopolitical landscape, the U.S. military is pursuing a suite of new strategies—blanketed under the title of the third offset strategy—in order to advance military dominance, which include: anti-access and area denial, guided munitions, undersea warfare, cyberwarfare, wargaming, and human-machine teaming (Eaglen, 2016; Work, 2015). In 2017, $201 million of the defense budget was allocated to human-machine teaming research and development alone (Eaglen, 2016). As agent technology continues to advance, allowing agents to act more intelligently and more autonomously, the relationship between the human and the agent will shift from Operator-Tool to mutual collaborators (Ososky et al., 2013; Phillips et al., 2011).

This shift in perspective, from agent as tool to agent as teammate, stems from their role in interactions with humans. Humans primarily use agents as individual support, to facilitate teamwork between humans, or as a functioning “virtual human” (Sycara & Sukthankar, 2006). In order to act as a “virtual human,” the agent must perform both task-specific skills as well as teamwork skills (Sycara & Sukthankar, 2006). Using teamwork skills allow team members to create and maintain the shared understanding needed to coordinate and act interdependently (Bradshaw et al., 2009; Phillips et al., 2011). Agents can simulate these teammate skills, and thus act as synthetic teammates, by supporting flexible automation strategy of mixed initiative interaction. (Chen & Barnes, 2014). Mixed initiative interaction refers to an interaction strategy between a human and a system where each supports joint actions and collaborative decision making by each contributing to the task what they do best (Allen et al., 1999; Chen & Barnes, 2014). This form of automation allows humans to delegate complex tasks to the agent, but doing so changes the nature of the task to one of management and facilitation (Parasuraman & Riley, 1997; Thompson, Whelan, & Coovert, 2009). When agents have the capability to act autonomously, in pursuit of their own goals, humans teamed with these complex systems may be locked out of the loop and may subsequently have difficulty understanding which factors influenced the agent’s actions and why (Chen et al., 2014; Chen & Barnes, 2014; Stubbs, Wettergreen, & Hinds, 2007). Consequently, human team members’ situation awareness must be taken into account when designing agents (Endsley & Jones, 2016; Kilgore & Voshell, 2014).

Situation Awareness and Teams

Situation Awareness (SA) refers to an individual's continuous diagnosis of factors within an ever-shifting environment (Parasuraman, Sheridan, & Wickens, 2008; Smith & Hancock, 1995). While multiple models have been developed to explain situation awareness, the most popular model of SA suggests that there are three phases to SA: perception of the elements in the environment, comprehension of the current situation, and projection of future status (Endsley, 1995). According to Endsley (1995), an individual's situation awareness equates to their situation model, that individual's constantly updated understanding of the current situation at any point in time (Cooke, Salas, Cannon-Bowers, & Stout, 2000; Endsley, 2015). This situation model is not only informed by the environment, but also by the individual's relevant mental models, as seen in Figure 1 (Endsley, 1995; Endsley, 2015). Furthermore, changes in the situation model can yield changes in mental models, which can change the actions an individual chooses to take (Endsley, 1995; Endsley, 2015). Exploring this constantly updating understanding or awareness becomes even more complicated in the context of a team (Salmon et al., 2008; Shu & Furuta, 2005).

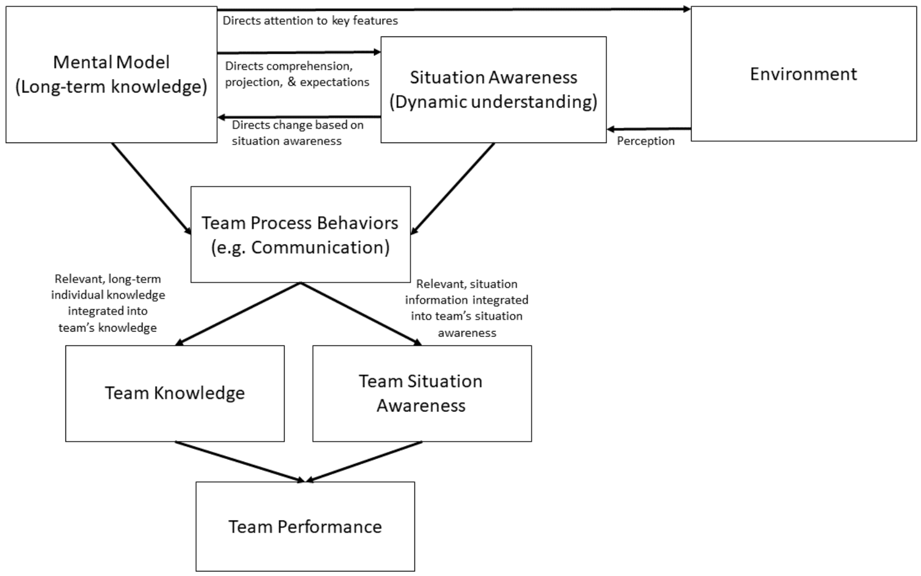


Figure 1. How individuals' mental models, individuals' situation awareness, and environment interact and influence team knowledge, team situation awareness, and team performance, adapted from Cooke et al (2004) and Endsley (1995; 2015)

A team is comprised of multiple actors, each of whom have their own situation models, mental models, and their own set of responsibilities (Cooke et al., 2004; Cooke, Stout, & Salas, 2001). Furthermore, different team members may have different responsibilities from their teammates and thus, subsequently, may focus on different aspects of the situation (Cooke et al., 2000; Cooke et al., 2004). In order for team members, who may have different situation and mental models, to be able to successfully pursue a shared objective, they must maintain a shared understanding of their situation (Salas, Sims, & Burke, 2005; Sycara & Sukthankar, 2006). Given the disparate sets of responsibilities, and prerequisite knowledge needed to fulfill them, that individual team members bring to the pursuit of a goal, a team's shared understanding of a situation does not require each team member to have identical knowledge (Cannon-Bowers &

Salas, 2001; Cooke et al., 2000). Instead, a team's shared understanding can be made up of individuals' compatible knowledge—knowledge that may differ between team members, but yields similar expectations in a situation (Cannon-Bowers & Salas, 2001). As seen in Figure 1, individual team members can engage in team process behaviors— such as communication, coordination, or planning—to integrate their individual situation models and relevant mental models with their teammates' to establish a shared knowledge and a shared awareness, which can influence the overall team's performance (Cooke et al., 2000; Cooke et al., 2004; Cooke et al., 2001).

The shift in paradigm from agents being characterized as tools to agents being characterized as teammates necessitates viewing the relationship more similarly to human teams (Ososky et al., 2013; Phillips et al., 2011). Agents using a mentalistic architecture establish their own model of the world, which they use to make decisions (Chen et al., 2018; Sycara & Sukthankar, 2006). An agent can use not only observation to build and update its world model, but it can also use its human team member as a source of information (Fong, Thorpe, & Baur, 2003; Kaupp, Makarenko, & Durrant-Whyte, 2010). For the human team member to use the agent as a source of information, the agent has to be designed to provide this information (Chen & Barnes, 2014; Endsley & Jones, 2016). Humans working with a "strong and silent" agent may have difficulties with situation awareness, increased workload, and increased performance error rates (Chen & Barnes 2014; Kilgore & Voshell 2014). Therefore, an agent that keeps humans apprised of its inner workings would keep human teammates in the loop, avoiding the deleterious effects of ignorance. However, the question of what specific information sharing requirements are needed to keep human teammates properly informed is still unanswered.

Transparency and Human-Agent Teamwork

By delegating tasks to automated systems, humans can accomplish more complex tasks without having to comprehend all parts of the more complex task (Miller, 2014; Zhu & Hou, 2009). As humans are able to delegate more tasks to more capable—and more complex—machines, they become further divorced from the tasks being accomplished (Chen & Barnes, 2014; Grote, Weyer, & Stanton, 2014). When humans are divorced from the tasks being accomplished, when they are out of the loop, they can exhibit an increased potential for error, higher cognitive load, lower trust in the system, and lower situation awareness (Grote et al., 2014; Kilgore & Voshell, 2014; Stubbs et al., 2007). While a system, whose internal processes are completely opaque to its human teammate, can cause this kind of difficulty for the overall team, a system that is more transparent can alleviate these problems (Kilgore & Voshell, 2014; Maass, 1983).

Transparency is an emergent property that results from human-system interaction, where the human can build an internal model of the system, allowing the human to see through its logic (Maass, 1983; Ososky et al., 2014; Stubbs et al., 2007). In a transparent interaction, the system is able to support the human's comprehension of relevant system information, so that both human and system are aware of this information (Chen et al., 2014; Karsenty & Botherel, 2005; Lyons et al., 2017; Sycara & Sukthankar, 2006).The content of this relevant information, however, can take many forms (Helldin et al., 2013). Some approaches to supporting transparent interaction include: disclosing system reliability (Wang, Jamieson, & Hollands, 2011), providing rationales for errors (Dzindolet, Peterson, Pomranky, Pierce, & Beck, 2003), and providing real time status updates (Zhou et al., 2016). These approaches to supporting transparency are relatively discrete and are appropriate for highly specific human-system interactions. For more complex systems, such as agents, more descriptive, model based approaches to supporting transparent interaction may be more appropriate.

Lyons (2013) suggests that transparent interaction can be supported by facilitating several dimensions of relevant information—intention behind the system, task-related information, the system's underlying analytical principles, environmental conditions, teamwork information, and the system's awareness of the human's state (Lyons & Havig, 2014; Lyons et al., 2017). Chen and associates (2014), on the other hand, focus on an established psychological framework, situation awareness, to specify the kind of information needed to support transparent interaction between humans and agents. The Situation awareness-based Agent Transparency (SAT) model establishes a breadth of information that can be communicated to the human without sacrificing flexibility, and thus will be further explored in this manuscript (Chen et al., 2014).

The SAT model (see Figure 2) supports transparency by informing the human operator's situation awareness (Chen et al., 2014). In the SAT model, a transparent system communicates three levels of information (Chen et al., 2014):

- Level 1 describes the agent's current actions, plans, and knowledge of its environment
- Level 2 describes the agent's underlying rationale behind its actions and plans
- Level 3 describes the agent's predictions about the outcomes of its planned actions and the uncertainties within those predictions

Figure 2. Situation Awareness based Agent Transparency (SAT) Model, adapted from Chen and associates' (2014) visualization of the SAT model

The SAT model has been successfully leveraged in human-agent interfaces to support the human's situation awareness and their calibration of trust in an agent in a human-agent team (Mercado et al., 2016; Selkowitz, Larios, Lakhmani, & Chen, 2017b; Wright, Chen, Barnes, & Hancock, 2016). Transparency has been supported through interface modules describing the three levels of SAT in an at-a-glance module, descriptions of the agent's understanding of the human's actions, and environmental field iconography (Selkowitz et al., 2017b). Retrospective analysis of this model and its implementation suggests that the SAT model, in this form, may not sufficiently meet the anticipated needs of complex military environments (Chen et al., 2018).

The SAT model was developed in a paradigm where autonomous agents were examples of silent, automated systems, and hence the SAT model was prescribed as a guide for developing more usable tools (Chen et al., 2014). Projected advances in agent technology have expanded the potential roles that agents can take, such that they can be expected to both commit tasks independently of a human operator and independently engage in part of a shared task with a human teammate (Barnes et al., 2017; Bradshaw et al., 2012; Chen et al., 2018). The U.S.

Department of Defense is shifting to a paradigm that emphasizes collaboration with autonomous agents, rather than the usage of a complex tool for a simple task (Defense Science Board, 2016; Sycara & Sukthankar, 2006; U.S. Army, 2017). This transition from an agent-as-tool paradigm to an agent-as-teammate paradigm necessitates a shift in the way human-agent teamwork and the factors that influence it are approached (Chen et al., 2018; Ososky et al., 2013; Phillips et al., 2011). Collaboration—defined as the pursuit of a shared goal through interdependent actions—implies that all collaborating parties have their own, independent models of the situation, so human collaboration with autonomous agents requires the maintenance of a shared awareness; this maintenance requires that the agent both gives information to and receives information from human teammates (Bradshaw et al., 2009; Bradshaw et al., 2012; Johnson et al., 2014). In response to this emphasis on human-agent collaboration, Chen and associates (2018) reviewed the SAT model and, using existing theories of teamwork, proposed a refinement of the SAT model known as the dynamic SAT model (Defense Science Board, 2016). The dynamic SAT model reframes transparent interaction by emphasizing the informational needs of human-agent teams engaging in shared tasks; while untested, this iteration of the SAT model (as seen in Figure 3) more strongly encompasses transactional feedback, emphasizing that transparency in a human-agent team requires two-way communication between the human and agent team members (Chen et al., 2018). The communication of information needed to maintain shared awareness is necessary when the human and agent teammates collaborate (Bradshaw et al., 2012; Chen & Barnes, 2014).

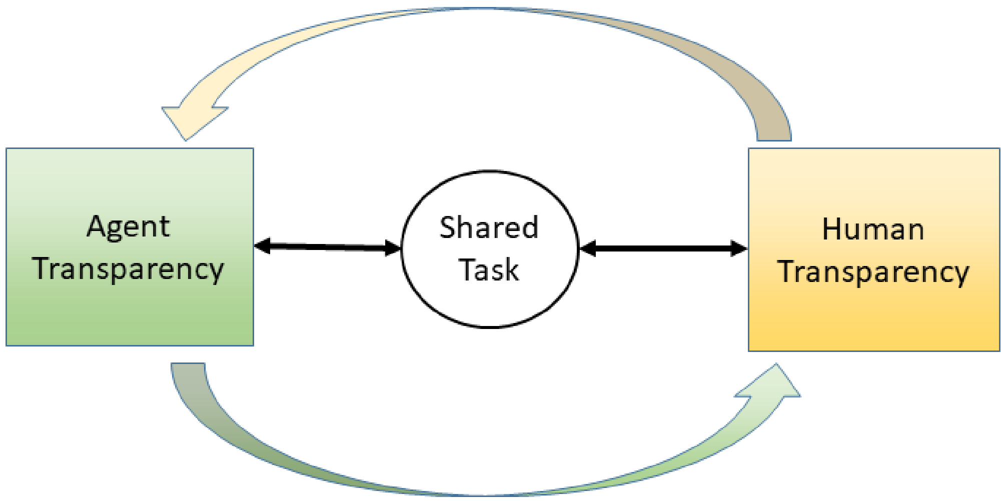


Figure 3. Dynamic SAT Model, adapted from Chen and associates (2018), detailing a bidirectional approach to transparency in human-agent teams. When engaging in a shared task, both human and agent team members must maintain transparency regarding their contributions to a shared task.

Communication, Team Cognition, and Transparency

Human teamwork can be a useful metaphor for human-agent teams, and consequently, research pertaining to human teams is a valuable stepping off point for human-agent teams (Morrow & Fiore, 2012). Sharing information has been a major concern for human-agent teams and human teams alike, so research concerning communication in human teams can be useful in informing research into communication for human-agent teams (Chen & Barnes, 2014; Gutzwiller & Lange, 2016; Sycara & Sukthankar, 2006). In human teams, communication is described as a reciprocal process where teammates send and receive information that form and reform the team's attitudes, behaviors, and cognitions (Salas et al., 2015). Forming and reforming relevant cognition is particularly important in dynamic environments, where the environment, and consequently team members' immediate understanding of the environment, is in flux (Cooke et al., 2000; Cooke et al., 2001).

Communication in teams is a major factor in Interactive Team Cognition (ITC) theory. ITC theory states that team interaction is cognitive activity at the team level (Cooke et al., 2013). This is in contrast to the shared cognition paradigm that ITC sprang from, where communication is a process by which individual team members share their individual models of the situation, creating a shared body of knowledge (Cooke et al., 2013; DeChurch & Mesmer-Magnus, 2010). In this approach, this shared body of knowledge can be used to develop shared expectations, allowing for improved team performance without explicit coordination (Cooke et al., 2013; MacMillan, Entin, & Serfaty, 2004).

The aforementioned descriptions of human team behavior, and the underlying factors, can be used to describe humans' interaction with artificial entities acting as team members, agents in this case (Sukthankar, Shumaker, & Lewis, 2012; Sycara & Sukthankar, 2006). Like a human team member, an agent acting as a team member shares information, about both task performance and teamwork, with the human members of their team (Gutzwiller & Lange, 2016; Lyons & Havig, 2014; Sycara & Sukthankar, 2006). The communication of rationale and other relevant information supports not only a transparent interaction between humans and agents, but also provides a pattern of communication from which team cognition emerges (Cooke, Demir, & McNeese, 2016; Gutzwiller & Lange, 2016).

In dynamic situations where the agent's responsibilities, and correspondingly its actions, can vary, interface elements can be used to maintain transparency and keep the agent's actions predictable (Hayes & Scassellati, 2013; Lyons, 2013; Nair, Tambe, & Marsella, 2003). In the context of ITC, transparency— evoked through the communication of goals, rationale, and projected outcomes—is the basis of a human-agent team's cognition. Interface elements, used to maintain transparency, dictate the kinds of interaction patterns available to the human-agent team, which, in turn, influence the team cognition that emerges from that interaction (Cooke et al., 2016; Fiore & Wiltshire, 2016).

Communication Patterns and Transactional Communication

Shannon, the father of information theory, describes how a message can be accurately transmitted from a message source to a receiver (Marko, 1973; McDonnell, Ikeda, & Manton, 2011). As seen in Figure 4, this model describes the transmission of information from a source to a receiver, through a possibly noisy channel.

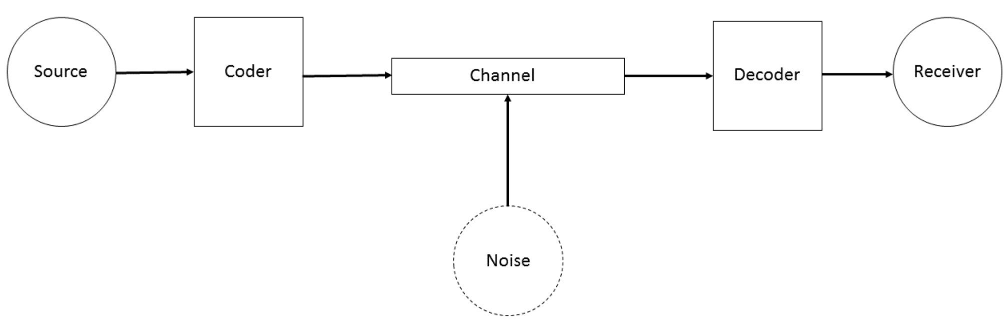


Figure 4. Unidirectional communication model, adapted from Marko (1973)

Marko (1973) extended Shannon's theory to describe bidirectional communication—where a message generator can transmit information along a communication channel to a second message generator who can also send information along a different communication channel to the initial message generator (see Figure 5).

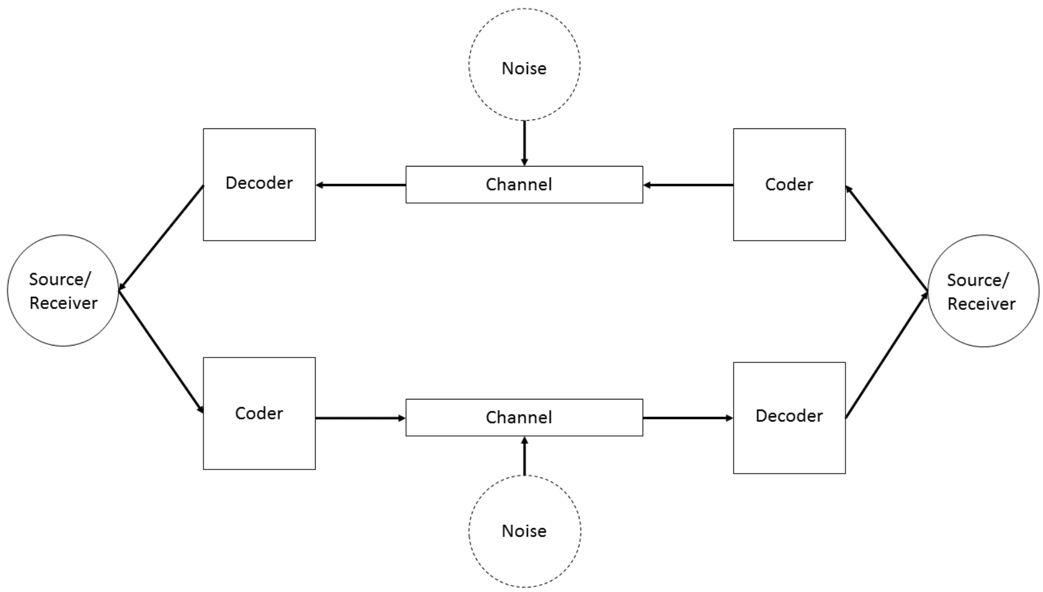


Figure 5. Bidirectional communication model adapted from Marko (1973)

In extant human-agent teams, these channels can be used by both human and agent team members to either solicit or provide information, depending on the capabilities of the agent (Kaupp et al., 2010; Sycara & Sukthankar, 2006). If the agent—often a variation of robotic agent—solicits information from the human team member, then that communication pattern can be referred to as robot-pull (Kaupp et al., 2010; Sweet, 2016). A robot-pull pattern can be a query for information or a request for guidance (Fong et al., 2003; Sweet, 2016). If the robot provides information, that communication pattern can be referred to as robot-push (Kaupp et al., 2010; Sweet, 2016). A robot-push pattern can be any variation of a robotic agent volunteering information to the human teammate (Kaupp et al., 2010; Sweet, 2016). Human team members can pull or push information as well, as long as the robot can interpret the input (Fong et al., 2005; Kaupp, 2008; Sweet, 2016). In human-pull patterns, humans can solicit information from the agent, while human-push ranges from volunteering information to assuming direct control over the agent or its priorities (Chen et al., 2018; Kaupp et al., 2010; Sweet, 2016).

Interpersonal communication, in the context of human teams, encompasses more than just the transfer of information between a sender and a receiver (Salas et al., 2015). Barnlund's transactional model of communication (see Figure 6) encompasses the factors that influence information sending, interpretation, and response by approaching communication as the mutual transmission of information between multiple communicators used to create a cumulative, shared meaning (Barnlund, 1970; Salas et al., 2015). Unlike bidirectional communication, transactional communication encompasses interactions where the communicators receive and build on each other's ideas, using a variety of cues (Foulger, 2004; Jurkowski & Hänze, 2015).

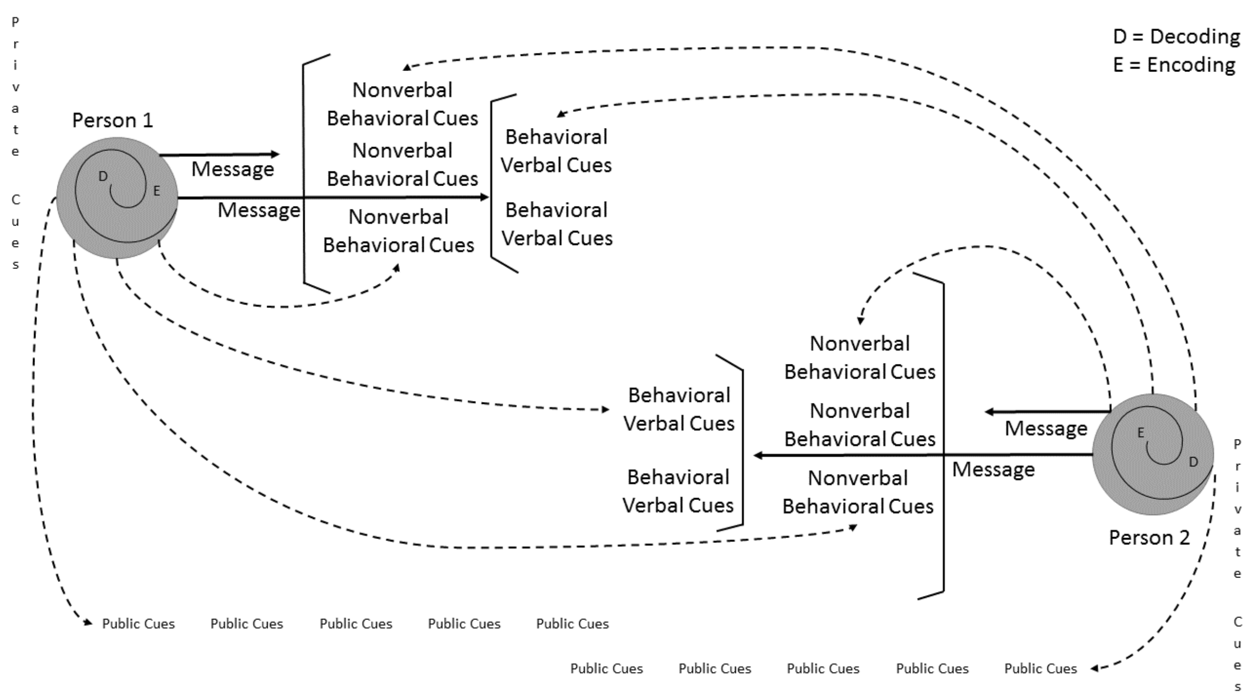


Figure 6. Transactional model of communication, adapted from Barnlund (1970)

In discussions of human communication and human teamwork, the reciprocal process by which human team members mutually transmit relevant information is a team process behavior known as communication (Salas et al., 2015). Team processes can be described as members' interdependent activities that convert inputs (e.g. individual taskwork knowledge, individual dynamic knowledge) to outcomes (e.g. team performance, behaviors) (Cooke et al., 2007; Marks, Mathieu, & Zaccaro, 2001; Mathieu, Maynard, Rapp, & Gilson, 2008; Salas et al., 2015).

A human-agent team, however, may not communicate like a human team does. Often, a unidirectional approach to communication is all that is needed to successfully complete the desired task—e.g. an agent continually pushing information to a human teammate, or a human operator teloperating a robot (Sheridan, 1995; Sycara & Sukthankar, 2006). A bidirectional approach may be useful in situations where an agent's role is to send information to a human but needs information or guidance from that human as well (Héder, 2014; Kaupp et al., 2010). In situations where humans and agents are interdependently completing a shared task, however, Chen and associates (2018) theorize that human and agent team members must mutually disclose relevant information to one another in order to complete their task effectively (Chen & Barnes, 2014). This is particularly relevant during shared tasks where the actions of one agent can influence the actions of the other.

As seen in Figure 1, human teams aggregate their individual situation awareness and mental models in order to create a shared understanding of the overall situation (Cooke et al., 2004). With the advent of more advanced, more mixed-initiative capable agents, these agents and their human teammates may benefit from establishing a similar shared understanding (Allen et al., 1999; Johnson et al., 2014). In order to create and update this understanding like human teams do, humans and agents in this situation need to be able to share information bidirectionally (Chen et al., 2018). With both human and agents able to act as sender and receiver, they are able to make the specific interchanges that allows for a shared understanding to be built (Olson-Wenneker, 2012). Mutual disclosure, meant to maintain a shared understanding of a situation, can be expressed as a dialogue between the human and the agent, with information reciprocally flowing between them in both directions (Hayes & Scassellati, 2013; Kaupp et al., 2010; Thrun, 2004). This dialogue can be used to facilitate the communication of information needed to predict future outcomes, allowing for the maintenance of compatible shared knowledge (Hayes & Scassellati, 2013; Héder, 2014). Communication, and the pattern of communication, can potentially impact attitudes, such as trust, towards agents (Chen & Barnes, 2014; Lee & See, 2004).

Trust and Attitudes Towards Automated Systems

In the context of human-agent teams, trust can be defined as "the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability" (Lee & See, 2004). In human teamwork, trust is an emergent state that influences training effectiveness, task conflict, and perception of a teammate's behavior (Mathieu et al., 2008; Salas et al., 2005). In the context of human-agent teaming, before the two actually interact, the human comes in with an initial propensity to trust or not trust machines (Merritt, Heimbaugh, LaChapell, & Lee, 2012). This propensity to trust can be an explicit attitude, and hence conscious, or an implicit attitude, and hence unconscious (Merritt et al., 2012).

One's trust in automated systems can influence the way that one reacts to the system, leading to issues regarding overtrust, undertrust, and trust calibration (Hancock et al., 2011; Merritt, Lee, Unnerstall, & Huber, 2015). Overtrust can lead to overreliance on the system, even in inappropriate situations, while undertrust can lead to underutilization of automation (Lee & See, 2004; Parasuraman & Riley, 1997). When the human is presented with accurate information about the agent, they should be able to match their expectations of the agent to its capabilities (Hancock et al., 2011). Accordingly, agent transparency should allow the human to calibrate their trust to its performance (Chen et al., 2018; Chen et al., 2014; de Visser, Cohen, Freedy, & Parasuraman, 2014).

A human's perception of an agent can influence how a human develops and maintains trust in an agent (Chen & Barnes, 2014; Sanders, Oleson, Billings, Chen, & Hancock, 2011). Bartneck and associates' (2009b) Godspeed Questionnaire Series details some of these perceptions that are often discussed in HRI work. Some of these perceptions attribute characteristics to an agent. Attribution of human form, characteristics, and behavior to non-human things (i.e. Anthropomorphism) or attribution of life or independent movement (i.e. Animacy) are common (Bartneck et al., 2009b). Nass and Moon (2000) suggest that even people who consciously reject anthropomorphizing computers still do so, while Schillaci and associates (2013) show that conveying information multimodally makes a robot seem more animate. A third perception, Likeability, can be defined as the extent to which a human forms a positive first impression of the agent (Bartneck et al., 2009b). In one study, where participants played a virtual basketball game with either a competent agent or a less competent but more communicative agent, participants liked the agent that non-verbally communicated with them more than the competent agent (Lala, Nitschke, & Nishida, 2015). Perceived intelligence, or the extent to which an agent is perceived to perform functions associated with intelligent human behavior, is another perception that humans can have about agents (Bartneck et al., 2009b). Computer agents have been perceived as less intelligent than an otherwise identical human agent in a decision making task (de Visser et al., 2016). An agent embodied in a more human-shaped container, however, was considered more intelligent than one embodied in a less human-like container (Bartneck, Kanda, Mubin, & Al Mahmud, 2009a). Finally, perceived safety refers to the human's perception of the level of danger when interacting with the agent (Bartneck et al., 2009b). Perceived safety was shown to be correlated to legibility (human understanding of agent's intention), a factor similar to transparency, in the context of a human crossing an embodied agent's path (Lichtenthäler & Kirsch, 2016).

Workload

Workload can be conceptualized as the perceived impact of task demand imposed on the human, as well as any corresponding physiological responses (Abich, 2013). Supporting transparency can lead to additional information on a visual display (Chen et al., 2014). This added information may influence the human's workload. Additional information may cognitively overload the operator, causing performance to suffer, but if that information mitigates its own presence by reducing workload caused by another part of the task, then the display can have this additional information without a noticeable increase in the human's workload (Chen et al., 2014; Hancock & Warm, 1989; Mercado et al., 2016). Workload, specifically perceived workload, will be measured using the National Aeronautics and Space Administration task load index (NASA-TLX) (Hart, 2006; Hart & Staveland, 1988).

Purpose for the Present Study

The SAT model has been used to outline the information an agent conveys to support a human teammates situation awareness of the agent (Chen et al., 2014; Mercado et al., 2016). However, when autonomous agents work with humans interdependently to accomplish a shared task, the knowledge requirements of humans and autonomous agents are different, especially when operating in a complex, continuously changing environment (Bradshaw et al., 2009; Chen et al., 2018; Johnson et al., 2014). Effective coordination among team members cannot take place without mutual knowledge of shared history, current status, and other common ground; each member—human and non-human—must be able to make good assumptions about what the others know and can do (Bradshaw et al., 2012). The common ground, or shared relevant knowledge, supports interdependent activity in a collaborative task (Bradshaw et al., 2009). When human teams engage in a shared task, they communicate information about the task and their teammates, which influences how the team will accomplish that shared task (Cooke et al., 2013; Mathieu et al., 2000; Salas et al., 2005).

When the SAT model is applied to a human and agent collaborating on a shared task in a rapidly changing environment, the dynamic SAT model can be used to represent the interdependent teamwork interactions and continuously updated teammate knowledge involved (Chen et al., 2018). Each team member needs to have a model of their own and their teammate's understanding of the shared task. The dynamic SAT model is a framework to understand the interactions and knowledge shared by human and agent teammates collaborating on a shared task. Given the importance of mutual information exchange—rather than feedback solely from one teammate to the other—to successfully accomplish a joint action, this study seeks to examine the influence that an agent query concerning the human's current state would have on a human who is completing a shared task with an agent (Bradshaw et al., 2009; Marks et al., 2001).

With the dynamic SAT model, both the agent's reasoning and the agent's understanding of the human's reasoning are made visible. While an agent's understanding can be plausibly based on inferences from observing the human's behavior, inquiries can be used to confirm the human's reasoning and foster long-term learning of human behavior. The current study also examines the effect of using an inference display—the at-a-glance module that is populated by information inferred by the agent through observation—versus using an inference display that is updated through queries to the human.

The goal for the current effort is to establish that transactional communication can improve human-agent collaboration in a shared task. The specific aims for this study are threefold. First, this study will determine the impact of transparency information regarding an embodied agent (i.e. robot) and its teammate. Pursuant to this aim, the effects of two approaches to supporting transparency are assessed: agent transparency and team transparency. Second, this study will investigate the impact of transactional communication facilitating transparency. Pursuant to this aim, two patterns of communication between a robot and a human will be explored: unidirectional communication and transactional communication. True transactional communication necessitates a continuous communication process, which is not currently feasible for this particular human-robot interaction, so the transactional communication condition will feature individual transactions between the human and robot, expressed as robot queries to the human teammate. Third, this study will compare human responses to communication patterns in situations where the robot reports information about itself and its understanding of the human teammate. In order to achieve these aims and subsequent objectives, the following will be assessed:

- Participants' situation awareness while working with a robot using differing communication patterns and different transparency support.
- Participants' implicit trust in automated systems (pre-study) and their current state of trust after working with a robot (post-task) with differing communication patterns and different transparency support.
- Participants' self-reported workload while interacting with a robot using different communication patterns and transparency support.
- Participants' accuracy in identification of stimuli and behavior as well as their response times, when working with robots with differing communication patterns and different transparency displays.

Hypotheses

Communication Pattern

1.1. When the robot queries participants, participants will exhibit more errors and greater response times when identifying targets, than when the robot does not query.

1.2. When the robot queries participants, participants will exhibit greater situation awareness, greater workload, greater trust in the robot (controlling for implicit trust), and improved attitudes towards the robot, than when they are not queried.

Table 1. Communication pattern hypotheses, AT: Agent Transparency, TT: Team Transparency, UC: Unidirectional Communication, TC: Transactional Communication, ↑: Higher, ↓: Lower.

	AT+UC	TT+UC	AT+TC	TT+TC
Performance & Error	↓	↓	↑	↑
Performance & RT	↓	↓	↑	↑
Situation Awareness	↓	↓	↑	↑
Workload	↓	↓	↑	↑
Trust	↓	↓	↑	↑
Attitude (GQS)	↓	↓	↑	↑

<u>Type of Transparency</u>

2.1. When the robot only supports agent transparency, participants will exhibit more errors and greater response times when identifying targets, than when they are presented with a robot that supports team transparency.

2.2. When the robot only supports agent transparency, participants will exhibit lower situation awareness, lower workload, lower trust in the robot (controlling for implicit trust), and worsened attitudes towards the robot, than when they are presented with a robot that supports team transparency.

Table 2. Type of transparency hypotheses, AT: Agent Transparency, TT: Team Transparency, UC: Unidirectional Communication, TC: Transactional Communication, ↑: Higher, ↓: Lower.

	AT+UC	TT+UC	AT+TC	TT+TC
Performance & Error	↑	↓	↑	↓
Performance & RT	↑	↓	↑	↓
Situation Awareness	↓	↑	↓	↑
Workload	↓	↑	↓	↑
Trust	↓	↑	↓	↑
Attitude (GQS)	↓	↑	↓	↑

Interactions

3.1. When the robot only supports agent transparency and queries participants, participants will exhibit more errors and greater response times when identifying targets, greater workload, and lower trust in the robot (controlling for implicit trust) than in the other conditions.

3.2. When the robot only supports agent transparency and does not query participants, they will exhibit lower situation awareness than in the other conditions.

3.3. When the robot supports team transparency and queries participants, they will exhibit more improved attitudes towards the robot in than the other conditions.

Table 3. Interaction between communication pattern and type of transparency hypotheses, AT: Agent Transparency, TT: Team Transparency, UC: Unidirectional Communication, TC: Transactional Communication, ↑: Higher, ↓: Lower.

	AT+UC	TT+UC	AT+TC	TT+TC
Performance & Error	↓	↓	↑	↓
Performance & RT	↓	↓	↑	↓
Situation Awareness	↓	↑	↑	↑
Workload	↓	↓	↑	↓
Trust	↑	↑	↓	↑
Attitude (GQS)	↓	↓	↓	↑

CHAPTER THREE: METHODOLOGY

Participants

According to a power analysis, conducted using the software application G*Power, a minimum of 36 participants will be needed to detect a medium-sized effect (f=0.25), given an alpha of .05, with a power criterion of .95. A total of 49 participants were recruited through UCF's IST Sona system, with 6 participants excluded from analysis due to either mechanical or experimenter error, 1 removed for providing incomplete information, and 2 removed as outliers, yielding 40 remaining participants. Thirteen men and 27 women participated in the study and their age averaged 21.13 (M_{age} = 21.13, SD = 3.95). These participants ranged from 18 to 43 years old, were U.S. citizens, and had adequate color vision, as determined through the Ishihara test (Appendix C) for color vision (Ishihara, 1960). Participants were compensated $15/hr for their participation.

Experiment Design

The experiment examined two variables. First, communication patterns, between a simulated robot and a human avatar operating interdependently in a simulated environment, were compared. Second, the type of information, in support of a transparent human-robot interaction, that the robot provides to the human teammate was also be compared. In order to examine these two variables, a 2 x 2 within-subjects design was employed. The independent variables were communication pattern (Communication Pattern: Unidirectional Communication, Transactional Communication) and type of transparency (Type of Transparency: Agent Transparency, Team

Transparency). This research design is described in Table 4. The order in which participants received these conditions was counterbalanced, using a Latin Squares randomization protocol.

Table 4. Experimental design for study. Conditions experienced by participants during a 2 (Transparency Type) x 2 (Communication Pattern) research design

	Unidirectional Communication	Transactional Communication
Agent Transparency	Agent Transparency + Unidirectional Communication	Agent Transparency + Transactional Communication
Team Transparency	Team Transparency + Unidirectional Communication	Team Transparency + Transactional Communication

Experiment Equipment

Two custom software applications was used to present the stimuli to participants on a standard desktop computer with two 22” monitors (1680 x 1050 resolution), standard keyboard, and three-button mouse (see Figure 7).

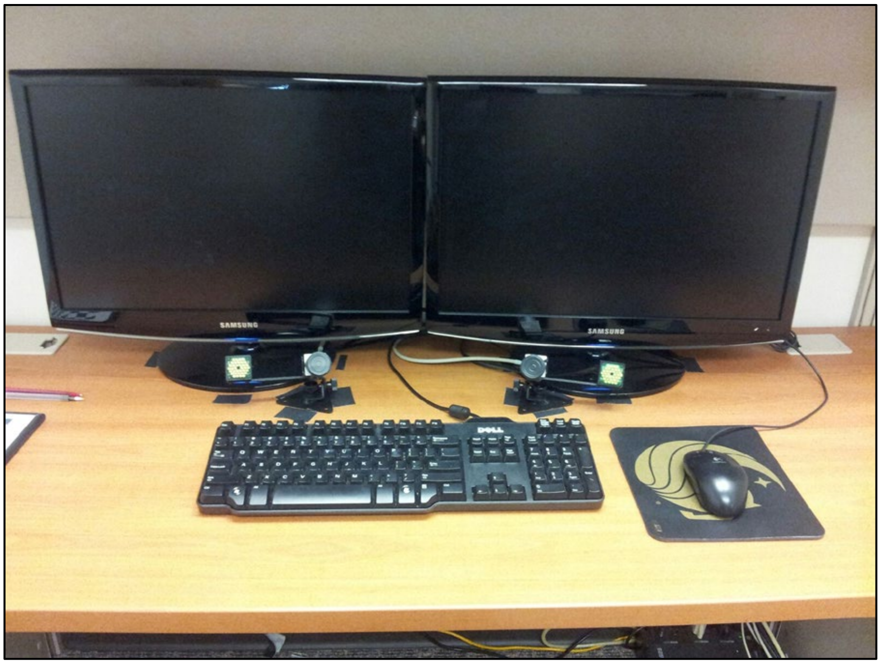


Figure 7. Experiment station with dual monitor set-up, standard keyboard, and three button mouse.

The first application, developed in the Unreal Engine 4 (UE4), was used to represent the physical environment and any subsequent events to the participant from a Soldier's point of view. Additionally, this application displayed a number of buttons corresponding to events they saw in this virtual environment. The display using UE4 can be seen in Figure 8.

Figure 8. Soldier's point of view (POV) screen. This screen depicts the virtual environment from the point of view of the Soldier as they observe the building that the robot is searching, as well as the surrounding area. Participants are asked to click on the relevant button when they see a person, a dangerous person, a vehicle, or a dangerous vehicle. If a vehicle obstructs their view, they are asked to click the obstacle button. If a person approaches the building, they are asked to click the intruder button.

The second application is adapted from a multimodal interface (MMI) prototype developed under the aegis of the Robotics Collaborative Technology Alliance (Barber et al., 2015; Barber, Howard, & Walter, 2016). The MMI was developed to allow users to communicate with a robot in real time (Barber et al., 2016). Users can send information to the robot via speech and gestures, while the robot can send information to the human using visual, auditory, and other channels (Barber et al., 2015; Barber et al., 2016). This study focused on the visual communication channel, using icons and clicking as the means of communication. This MMI displayed information from the robot's point of view, including information about the robot's current goals, priorities, and projected outcomes. The second display, using the second application, can be seen in Figure 9 and Figure 10.

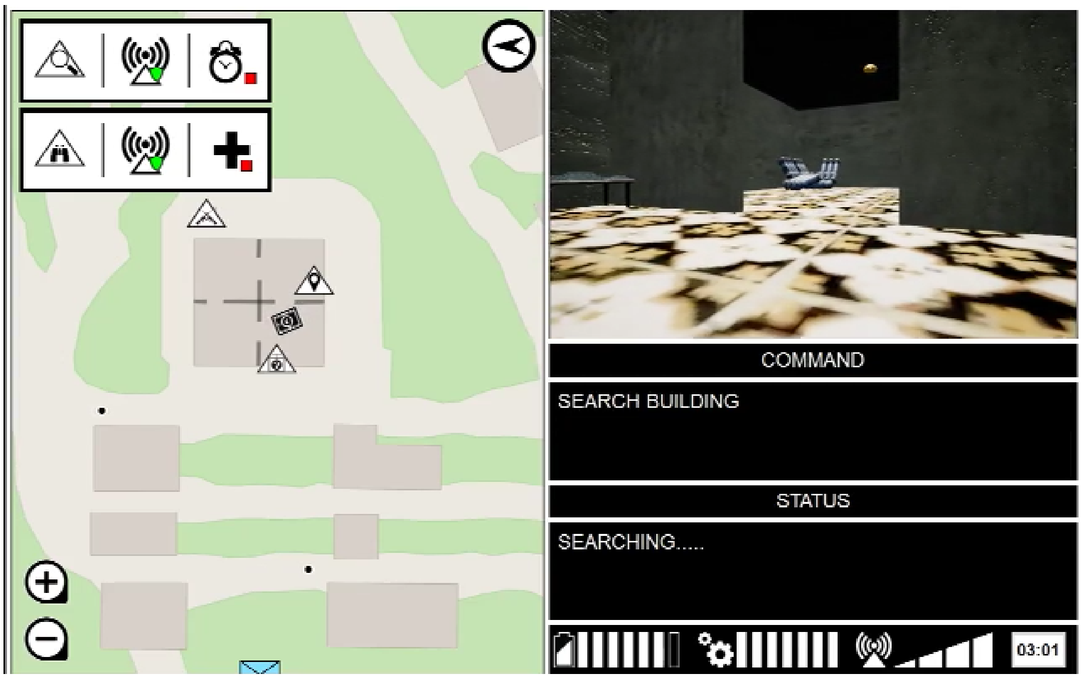


Figure 9. The human-robot interaction interface. This projected interface includes a dynamic map (left), a feed from the robot's view (top right), at-a-glance modules supporting both agent transparency (left, top icon set) and team transparency (left, bottom icon set), a feed from command and current status (middle right), and an area where the robot can make inquiries to its human teammate (bottom right).

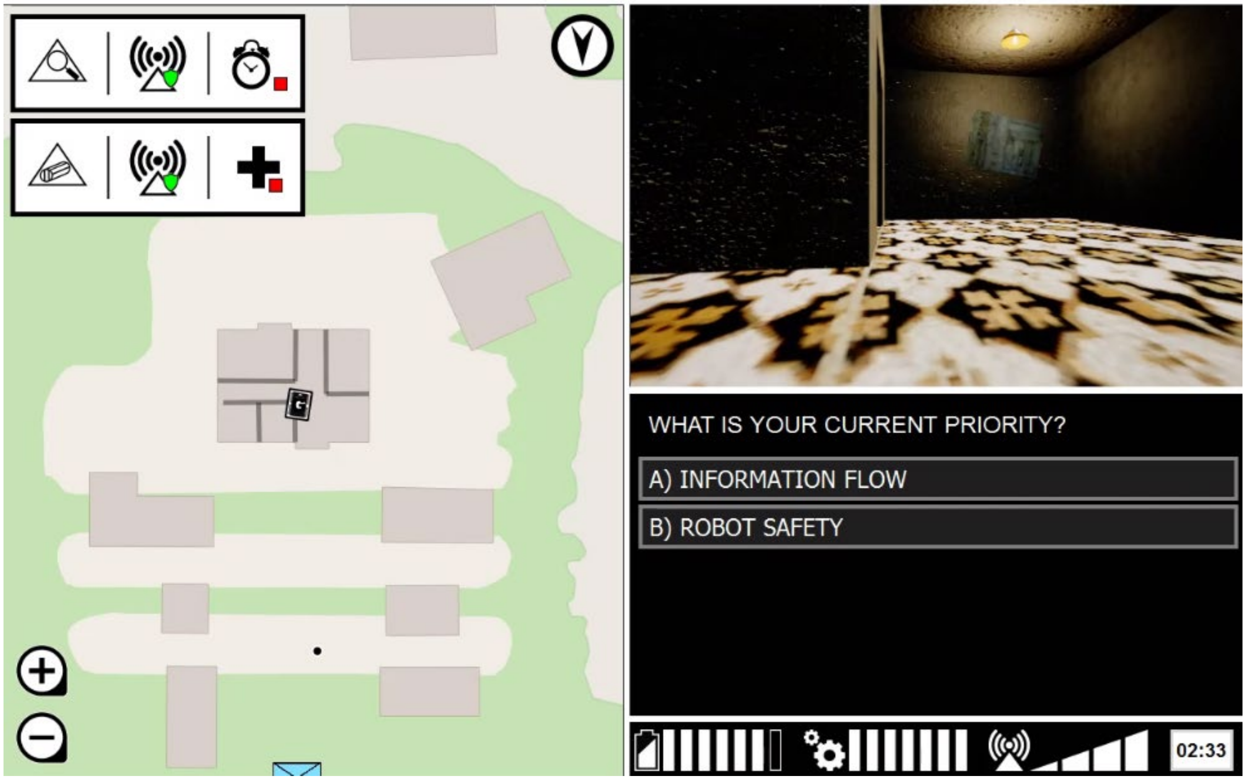


Figure 10. The human-robot interaction interface, making a transactional query. In Transactional Communication conditions, the feed from command and current status modules (middle right) are periodically replaced with a transactional query, where the robot asks the human teammates about their rationale.

Independent Variables

Communication Pattern

Two types of communication patterns were examined in this study: Unidirectional Communication and Transactional Communication. In the Transactional Communication condition, the robot periodically asked the participant, using a query, to confirm their rationale in the simulation (see APPENDIX E). In the Unidirectional Communication condition, the agent did not inquire about the human’s current rationale. The differences between these conditions are displayed in Figure 11.

Figure 11. Transparency design layout for the different conditions

Type of Transparency

Two types of transparency were examined in this study: agent transparency and team transparency. In the agent transparency condition, the robot displayed information pertaining to its own current goal, rationale, and projected future state. In the team transparency condition, the robot displayed information pertaining to both its own current goal, rationale, and projected future state as well as its understanding of the human’s current goal, rationale, and projected future state. The differences between these conditions are displayed in Figure 11.

Dependent Variables

Performance Measures

Classification Accuracy

Classification accuracy is recorded based on the participants' clicking of a button on the Soldier POV screen using a mouse. If the participant presses the button that correctly corresponds with the event presented to them, that result will be scored as correct. This result was reported for each participant, per condition, in terms of total number of correct identifications in each condition. If the participant presses the wrong button, then that result will be scored as an incorrect identification. If the participant does not press any button, then that result is classified as a miss. These results are reported for each participant, per condition, as the total number of identifications made or missed.

Reaction Time

Reaction time is recorded based on the speed of the participants' clicking of the correct button on the Soldier POV screen. The reaction time recorded will be from the time the event occurs, depicted in the UE4 software application, to the time the participant presses the corresponding button. If the participant does not press the corresponding button, then it will be marked as a missing value and will be struck from the list of response times that will be used to compose the final measure. The measure reported for each participant, per condition, will be median reaction time for all correct identifications.

Questionnaires and Surveys

Demographic Questionnaire

A demographics questionnaire was administered to participants at the beginning of the experimental session (see APPENDIX B). This measure includes items related to age, gender, video game expertise, military experience, and experience with robots.

Color Vision

Participants were asked to complete an Ishihara color vision test before beginning the study (see APPENDIX C). The Ishihara color vision test that was used in this study is comprised of nine plates, each of which displays a circle of dots, within which a pattern of dots show a number visible to those with normal color vision (Ishihara, 1960). Identifying fewer than seven of the nine plates correctly was grounds for removal from the study.

Situation Awareness

Participants received Situation Awareness probes during pre-determined freezes of the simulation during the task under analysis (Jones & Kaber, 2004; Salmon et al., 2009; Stanton, Salmon, & Rafferty, 2013). During a simulation, the displays were blanked and the participants' knowledge of SA elements were elicited (Stanton et al., 2013). A total of five freezes occurred during each condition, with each freeze being comprised of ten questions. The final measure reported for each participant, per condition, was percentage of SA questions correct out of total presented, for each level of SA. An overall SA score was determined by assessing percentage of

SA queries correct out of total presented, per condition. SA questions that were asked during freeze probes can be seen below (APPENDIX D).

Trust in Automated Systems

To measure a person's state of trust in an agent, Jian and associates' (2000) Checklist for Trust between People and Automation was used. The twelve questions in the checklist, answered using 7-point Likert-type scales was used to assess the human's state of trust at the end of each scenario (APPENDIX F). When scoring this measure, five of the twelve items must be reverse coded. After these items were reversed, the resulting seven point Likert-type scores were averaged together to create a mean trust score for each block.

Implicit Attitude Toward Automated Systems

Implicit attitude towards automation, defined as the positivity of an individual's mental associations with the concept of automation, can be measured using a variant of the Implicit Attitude Test (Merritt et al., 2012). Implicit Attitude Tests (IATs) use response latencies to measure implicit associations, with shorter response latencies representing stronger associations, and thus, a stronger preference (Greenwald, Nosek, & Banaji, 2003; Nosek, Greenwald, & Banaji, 2005). Before starting the experimental tasks, participants were given superordinate categories—good, bad, human, person, automation, and machine in this instance—and they were asked to associate "good" (e.g. Love, Peace) and "bad" (e.g. Hurt, Evil) words with those categories (see APPENDIX G). Participants received two blocks where "automation" was associated with "good" and "human" was associated with "bad" and two blocks where “automation” was associated with “bad” and “human” was associated with “good.” Half the participants received the “automation” and “good” associations first, while the other half of the participants received the “automation” and “bad” associations first, to counteract any systemic order effects. The scoring algorithm used the difference in mean response times between two opposite response blocks (e.g. Automation & Bad – Automation & Good) and divided that by the pooled standard deviation of those two blocks (Greenwald et al., 2003). The quotients for both sets of opposite response blocks were averaged to create something similar to an effect size measure, with the final result being either a negative score, which indicates a stronger association between automation and “good,” or a positive score, which indicates a stronger association between automation and “bad.” These scores were used to determine how the participants’ implicit attitude towards automation influences their trust in the automated systems they were exposed to.

Workload

This study measured participants’ perceived workload using the NASA Task Load Index (Hart & Staveland, 1988). The NASA-Task Load Index is a six item task load index (Hart, 2006; Hart & Staveland, 1988) which provides workload assessment specific to mental demand, physical demand, temporal demand, performance, effort, and frustration, as well as a single combined measure of global workload based on the mean of the six subscales. Each subscale is scored between 0 and 100, with 0 being low perceived workload and 100 being high perceived workload. This measure (in APPENDIX H) was administered through a standard computer program after each scenario.

Godspeed Questionnaire Series

The Godspeed Questionnaire Series (GQS) comprises 24 questions in five scales that evaluates user opinions of social aspects of a robot during a human-robot interaction task: anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety. The GQS items are rated according to a five-point Likert scale with end points that are semantic differentials (e.g., Awful/Nice). The results yielded five mean scores, each corresponding to a different subscale. This measure (available in APPENDIX I) was administered through a standard computer program after each scenario.

Procedure

After being briefed on the purpose of the study and signing the informed consent form, participants were tested for normal color vision using the Ishihara Color Vision Test. Failure to pass the Ishihara Color Vision test (identifying fewer than seven of the nine color plates successfully) was grounds for dismissal from the study. Participants who passed the Ishihara Color Vision test completed the demographics questionnaire and implicit trust measure. Once these measures were completed, participants were randomly assigned to one of four counterbalanced experimental blocks. They were then given a training slideshow to familiarize themselves with the display characteristics and the expectations from a cordon and search-like task. This training was split into sections, each detailing an individual aspect of the experimental task, culminating in a final practice scenario. During training, participants went through a series of multiple choice evaluations, one after each section, to confirm that they have understood the material that has been trained. If the participant scored 80% or more on an evaluation, they continued to the next section of training. If the participant scored less than 80% on one of these evaluations, they were asked to review the material. Scoring less than 80% on a single evaluation three times in a row was grounds for dismissal from the study. This process continued until the participant reached the final section, a mock scenario. Participants who scored at least 80% on this cumulative evaluation successfully completed the training. Following the final training evaluation, participants completed a training scenario, using the UE4 and MMI.

Afterwards, participants began the experimental conditions. In the experimental task, the participant worked with a simulated robot in a series of squad level cordon and search-like tasks. The participant observed two monitors, one displaying a simulated environment, the other displaying a robot interface. The robot acted as a search element, exploring a building for high-value targets. During this scenario, the robot encountered events, which affected its goals, rationale, and projected future state. Using the robot's interface, the human monitored the robot's actions while simultaneously acting as a cordon element, identifying pre-specified stimuli of interest in the simulated environment. Jointly, the human and the robot kept people out of the building; the participant was tasked with alerting the robot when individuals approach the building's entrance and the robot chased away any intruders who enter the building. During each scenario, participants received probes concerning their awareness of the situation. In transactional query conditions, the participant was presented with a query on the robot's interface while the participant identified stimuli, asking them what their current rationale was.

There were four separate scenarios, each of which represented one combination of communication pattern and transparency. Each scenario, absent any surveys or questions, lasted approximately 6 minutes. During each scenario, participants received 5 freeze point probes, comprised of 10 SA questions, distributed throughout the scenario. After each scenario, participants took the NASA Task Load Index (Hart & Staveland, 1988), the Jian trust in automated systems scale (Jian, Bisantz, & Drury, 2000), and the GQS (Bartneck et al., 2009b). After completing all scenarios, the participant was thanked for participation and any questions they had pertaining to the study was answered. The entire session took at most 4 hours.

CHAPTER FOUR: ANALYSIS

Data analysis was performed using SPSS Version 23. In this experiment, 2 (communication pattern: unidirectional, transactional) x 2 (transparency type: agent transparency, team transparency) repeated measures ANOVAs ($\alpha = .05$) were performed to determine the independent variables' effects on the dependent variables, unless stated otherwise. Effect size was reported using omega squared (ω^2).

Descriptive Statistics

Participants were asked about their level of education. Most participants reported some college experience (77.5%), with the remaining reporting that they completed high school (7.5%), completed an associate's or technical degree (7.5%), or completed a Bachelor's degree (7.5%). Over half the participants needed to wear some form of corrective lens (60%), with 37.5% wearing glasses and 22.5% wearing contact lenses. No participants reported a color vision deficiency.

Participants were also asked about their experience with computers and robots. The majority of participants felt comfortable using several software packages (45%), while fewer participants felt comfortable using only one type of software package (27.5%) or felt comfortable using multiple software packages and programming in one computer language (25%). Only one participant (2.5%) described themselves as a novice computer user. Participants reported that their average weekly computer use ranged between 10 to 84 hours per week ($M = 32.28$, $SD = 20.72$), so the vast majority of participants were comfortable using computers. However, that comfort did not extend to robots. Overall, participants rated their experience with robots ($M =$

1.93, *SD* = 0.86, out of 5) and their knowledge regarding robotics technology (*M* = 1.40, *SD* = 0.71, out of 5) as relatively low.

Implicit Attitude Toward Automated Systems

Before undergoing any scenario, participants completed an implicit attitude test to determine their implicit attitude toward automation. Participants' reaction time was used to determine a D score, where a positive D score denotes a negative attitude toward automation and, conversely, a negative D score denotes a positive attitude toward automation. After each scenario, participants were asked to rate their trust in the automated system with which they had worked.

Counter to expectations, the order of association ("automation" and "good" first vs. "automation" and "bad" first) had a significant effect on IAT score ($F(1,39) = 103.63$, $p < .01$). A one-way ANOVA revealed participants who first saw "automation" and "good" (*M* = -0.34, *SD* = 0.34) reported a more positive view of automation than those who first saw "automation" and "bad" (*M* = 0.55, *SD* = 0.52). Table M - 1 provides descriptive statistics for IAT scores. To facilitate the analysis of this data, along with post-scenario trust data, z-scores for these two groups of people were calculated (see

Table M - 2 for more information). A one-way ANOVA revealed no significant difference between these groups ($F(1,39) = 0.01$, $p = .94$). Correlation between standardized IAT scores revealed weak relationships between IAT scores and the post-scenario trust scores, none of which were significant (see Table M - 3 for more information). Due to the unexpectedly low correlation between these factors, standardized IAT scores were blocked—scores under 0 (N = 21) were compared to scores above 0 (N = 19).

Communication Pattern

Performance: Classification Accuracy

Participants' correct identifications were determined by the number of times the participant clicked on the correct button in response to a model or behavior on screen. The maximum number of correct identifications a participant could make, per scenario, was 28. Participants' correct identification count, and other descriptive statistics, is available in Table J - 1. Incorrect identifications are defined by participants responding to a stimulus on the screen by clicking on the wrong button. Participants, overall, made relatively few errors (see Table J - 2 for descriptive statistics). A miss is defined as a participant not clicking any button after six seconds of exposure to the stimulus. Overall, participants rarely missed identifying an event (see Table J - 3 for descriptive statistics).

In terms of correct identifications, a main effect for communication pattern was revealed—$F(1, 39) = 5.55$, $p = .02$, $\omega^2 = .06$. As seen in Figure 12, when participants were exposed to a non-querying agent interface ($M = 26.94$, $SD = 2.71$), they answered slightly more accurately than when they were exposed to a querying agent interface ($M = 26.49$, $SD = 3.07$). In terms of incorrect identifications, no main effect for communication pattern were exhibited, $F(1, 39) = 2.27$, $p = .14$, $\omega^2 = .02$).

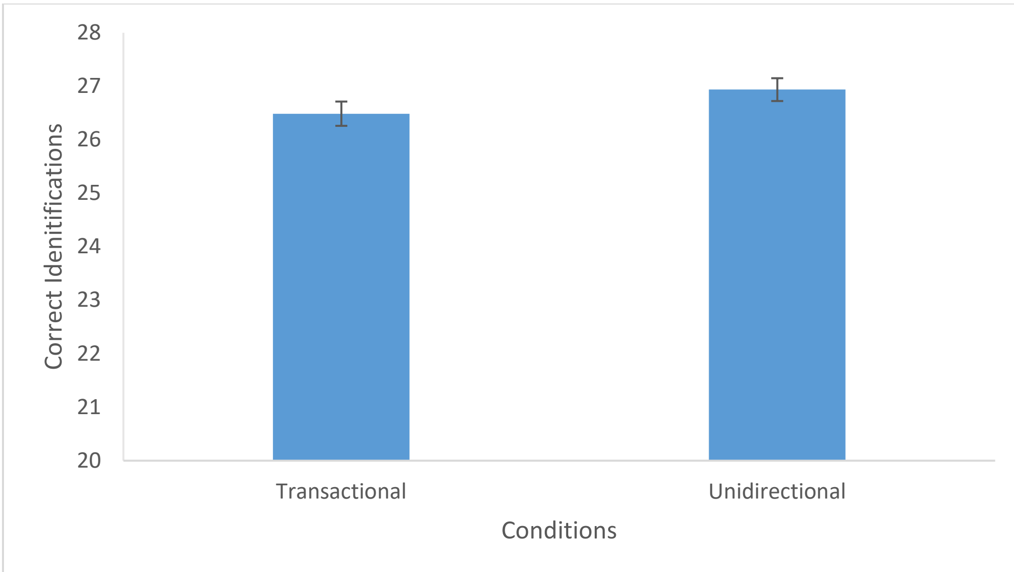


Figure 12. Mean classification accuracy comparison of Transactional and Unidirectional Communication Pattern combinations. Error bars represent standard error.

In terms of misses, a main effect for communication pattern was revealed—$F(1, 39) = 4.37$, $p = .04$, $\omega^2 = .03$. As seen in Figure 13, when participants were exposed to a querying agent interface ($M = 1.15$, $SD = 2.27$), they missed more events than when they were exposed to a non-querying agent interface ($M = 0.84$, $SD = 1.93$).

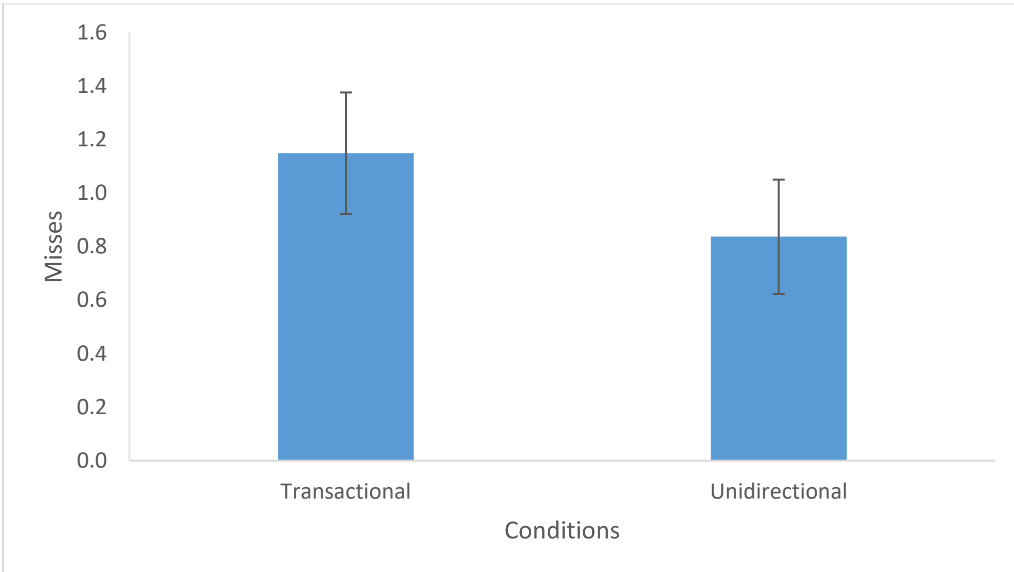


Figure 13. Mean error comparison of Transactional and Unidirectional Communication Pattern combinations. Error bars represent standard error.

Performance: Reaction Time

Participants' reaction time was determined by the median time that participants took to select the correct answer in response to a model or behavior on screen during a scenario. In terms of reaction time, no main effect for communication pattern ($F(1, 39)$ = 1.45, p = .24, ω^2 = .00) was exhibited. See Table J - 4 for descriptive statistics.

Situation Awareness

Situation awareness refers to the percentage of SA questions that participants answered correctly during a scenario. The score for overall situation awareness was determined by pooling participants' SA Level 1, SA Level 2, and SA Level 3 scores together and creating an average. SA Level 1 refers to the percentage of Level 1 SA questions answered correctly during a scenario. SA Level 2 refers to the percentage of Level 2 SA questions answered correctly during a scenario. SA Level 3 refers to the percentage of Level 3 SA questions answered correctly during a scenario.

In terms of overall SA, no main effect for communication pattern ($F(1, 39) = 0.00$, $p = .99$, $\omega^2 = .00$) was exhibited. See Table K - 1 for descriptive statistics. In terms of SA Level 1, no main effect for communication pattern ($F(1, 39) = 0.19$, $p = .66$, $\omega^2 = .00$) was exhibited. See Table K - 2 for descriptive statistics. In terms of SA Level 2, no main effect for communication pattern ($F(1, 39) = 0.05$, $p = .82$, $\omega^2 = .00$) was exhibited. See Table K - 3 for descriptive statistics. In terms of SA Level 3, no main effect for communication pattern ($F(1, 39) = 0.05$, $p = .82$, $\omega^2 = .00$) was exhibited. See Table K - 4 for descriptive statistics.

Overall Workload

Workload describes participants' unweighted global workload score as determined by their responses on the NASA-TLX after each scenario. Responses to each subscale were averaged together to create an estimate of overall workload, an approach which has been referred to as Raw TLX (Hart, 2006). In terms of overall workload, no main effect for communication pattern ($F(1, 39) = 1.02$, $p = .32$, $\omega^2 = .00$) was exhibited. See Table L - 1 for descriptive statistics.

Trust

Trust was measured using Jian and Associates' (2000) Trust in Automated Systems survey after each scenario. IAT block was used as a between-subjects factor. A mixed-factorial ANOVA was performed to determine the effect of transparency and communication pattern on trust in the robot, and how incoming attitude toward automation influences this trust. In terms of post-scenario trust, no main effect for communication pattern ($F(1, 38)$ = 1.27, p = .27, ω^2 = .00) was exhibited. See Table M - 4 for descriptive statistics.

Godspeed Questionnaire Series

The Godspeed Questionnaire Series was used to determine the attitudes that participants held towards the robot with which they worked. Participants were instructed that, in each condition, they worked with a different robot, so the questionnaire series was administered after each condition. Anthropomorphism was measured using the Anthropomorphism subscale of the Godspeed Questionnaire Series (Bartneck et al., 2009b). Participants did not anthropomorphize any one of the robots in the four conditions significantly more than any of the others. .Specifically, no main effect for communication pattern ($F(1, 39)$ = 0.74, p = .40, ω^2 = .00) was exhibited. See Table N - 1 for descriptive statistics.

Animacy was measured using the Animacy subscale of the Godspeed Questionnaire Series (Bartneck et al., 2009b). Participants' specific animacy attribution values are available in Table N - 2. In terms of animacy, a main effect for communication pattern was revealed, $F(1, 39)$ = 5.90, p = .02, ω^2 = .07. As seen in Figure 14, when participants worked with a non-querying agent interface (M = 2.67, SD = 0.75), they rated the robot as less animate than its querying counterpart (M = 2.87, SD = 0.64).

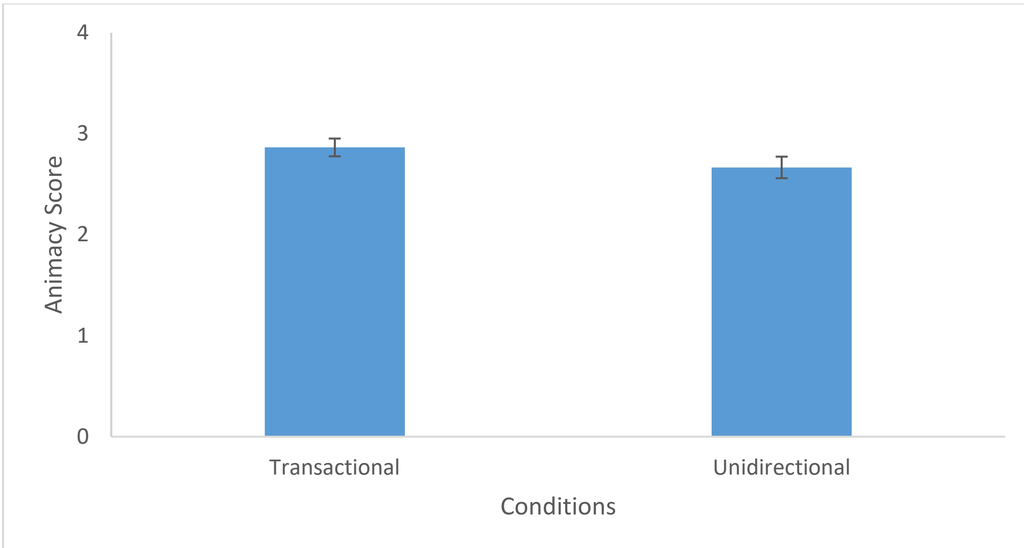


Figure 14. Mean Animacy score of Transactional and Unidirectional Communication Pattern combinations. Error bars represent standard error.

Likeability was measured using the likeability subscale of the Godspeed Questionnaire Series (Bartneck et al., 2009b). Participants' specific likeability attribution values are available in Table N - 3. In terms of likeability, a main effect for communication pattern was revealed, $F(1, 39) = 4.17$, $p = .05$, $\omega^2 = .06$. As seen in Figure 15, when participants worked with a non-querying agent interface ($M = 3.14$, $SD = 0.10$), they rated it as less likeable than its querying counterpart ($M = 3.33$, $SD = 0.08$).

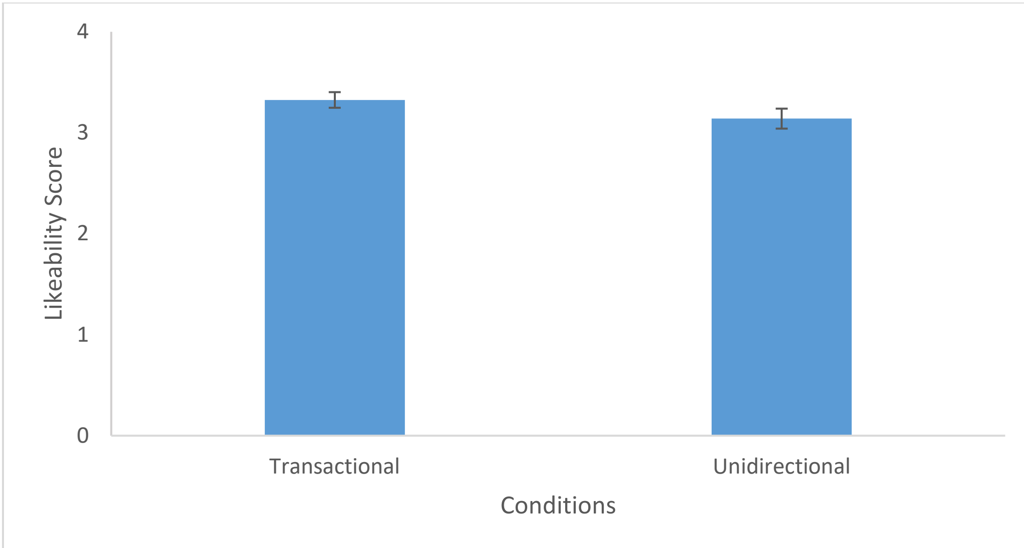


Figure 15. Mean Likeability score of Transactional and Unidirectional Communication Pattern combinations. Error bars represent standard error.

Perceived intelligence was measured using the perceived intelligence subscale of the Godspeed Questionnaire Series (Bartneck et al., 2009b). Participants' specific perceived intelligence values are available in Table N - 4. In terms of perceived intelligence, a main effect for communication pattern was revealed, $F(1, 39) = 5.49$, $p = .02$, $\omega^2 = 0.08$. As seen in Figure 16, when participants worked with a non-querying agent interface ($M = 3.67$, $SD = 0.11$), they perceived it as less intelligent than its querying counterpart ($M = 3.91$, $SD = 0.08$).

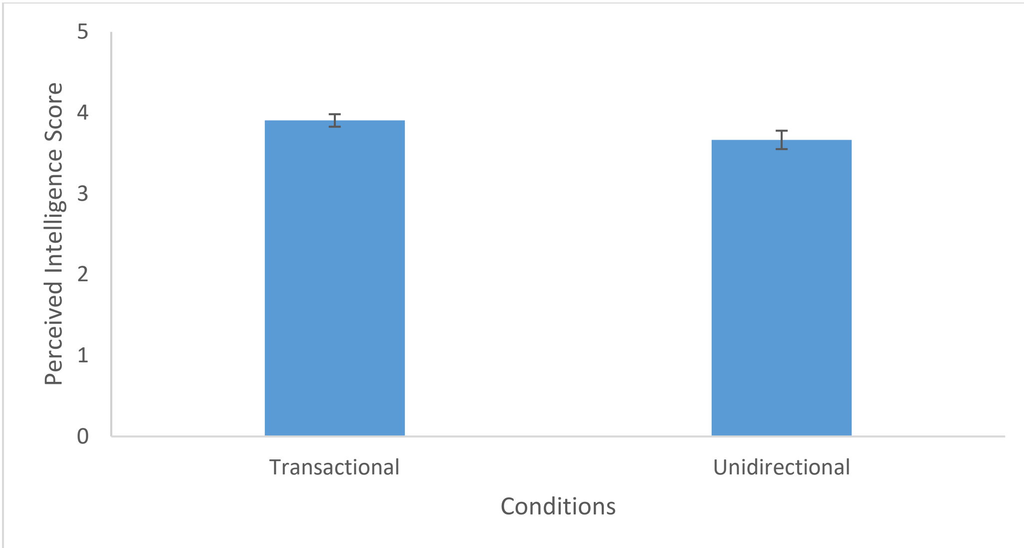


Figure 16. Mean Perceived Intelligence score of Transactional and Unidirectional Communication Pattern combinations. Error bars represent standard error.

Perceived Safety was measured using the perceived safety subscale of the Godspeed Questionnaire Series (Bartneck et al., 2009b). In terms of perceived safety, no main effect for communication pattern ($F(1, 39) = 0.40$, $p = .53$, $\omega^2 = .00$) was exhibited. See Table N - 5 for descriptive statistics.

Type of Transparency

Performance: Classification Accuracy

Participants' correct identifications were determined by the number of times the participant clicked on the correct button in response to a model or behavior on screen. The maximum number of correct identifications a participant could make, per scenario, was 28. Participants' correct identification count, and other descriptive statistics, is available in Table J - 1. Incorrect identifications are defined by participants responding to a stimulus on the screen by clicking on the wrong button. Participants, overall, made relatively few errors (see Table J - 2 for descriptive statistics). A miss is defined as a participant not clicking any button after six seconds of exposure to the stimulus. Overall, participants rarely missed identifying an event (see Table J - 3 for descriptive statistics).

In terms of correct identifications, no main effect for transparency was revealed, $F(1, 39) = 0.52$, $p = .48$, $\omega^2 = .00$. In terms of incorrect identifications, no main effect for transparency ($F(1, 39) = 0.02$, $p = .89$, $\omega^2 = .00$) was exhibited. In terms of misses, no main effect for transparency was revealed, $F(1, 39) = 1.06$, $p = .39$, $\omega^2 = .00$.

Performance: Reaction Time

Participants' reaction time was determined by the median time that participants took to select the correct answer in response to a model or behavior on screen during a scenario. In terms of reaction time, no main effect for transparency ($F(1, 39) = 2.01$, $p = .16$, $\omega^2 = .01$) was exhibited. See Table J - 4 for descriptive statistics.

Situation Awareness

Situation awareness refers to the percentage of SA questions that participants answered correctly during a scenario. The score for overall situation awareness was determined by pooling participants' SA Level 1, SA Level 2, and SA Level 3 scores together and creating an average. SA Level 1 refers to the percentage of Level 1 SA questions answered correctly during a scenario. SA Level 2 refers to the percentage of Level 2 SA questions answered correctly during a scenario. SA Level 3 refers to the percentage of Level 3 SA questions answered correctly during a scenario.

In terms of overall SA, no main effect for transparency ($F(1, 39) = 0.15$, $p = .70$, $\omega^2 = .00$) was exhibited. See Table K - 1 for descriptive statistics. In terms of SA Level 1, no main effect for transparency ($F(1, 39) = 0.88$, $p = .36$, $\omega^2 = .00$) was exhibited. See Table K - 2 for descriptive statistics. In terms of SA Level 2, no main effect for transparency ($F(1, 39) = 3.48$, $p = .07$, $\omega^2 = .05$) was exhibited. See Table K - 3 for descriptive statistics. In terms of SA Level 3, no main effect for transparency ($F(1, 39) = 3.48$, $p = .07$, $\omega^2 = .05$) was exhibited. See Table K - 4 for descriptive statistics.

Overall Workload

Workload describes participants' unweighted global workload score as determined by their responses on the NASA-TLX after each scenario. Responses to each subscale were averaged together to create an estimate of overall workload, an approach which has been referred to as Raw TLX (Hart, 2006). In terms of overall workload, no main effect for transparency ($F(1, 39) = 3.29$, $p = .08$, $\omega^2 = .03$) was exhibited. See Table L - 1 for descriptive statistics.

Trust

Trust was measured using Jian and Associates' (2000) Trust in Automated Systems survey after each scenario. IAT block was used as a between-subjects factor. A mixed-factorial ANOVA was performed to determine the effect of transparency and communication pattern on trust in the robot, and how incoming attitude toward automation influences this trust. In terms of post-scenario trust, no main effect for transparency ($F(1, 38) = 2.84$, $p = .10$, $\omega^2 = .02$) was exhibited. See Table M - 4 for descriptive statistics.

Godspeed Questionnaire Series

The Godspeed Questionnaire Series was used to determine the attitudes that participants held towards the robot with which they worked. Participants were instructed that, in each condition, they worked with a different robot, so the questionnaire series was administered after each condition. Anthropomorphism was measured using the Anthropomorphism subscale of the Godspeed Questionnaire Series (Bartneck et al., 2009b). Participants did not anthropomorphize any one of the robots in the four conditions significantly more than any of the others. Specifically, no main effect for transparency ($F(1, 39) = 1.93$, $p = .17$, $\omega^2 = .01$) was exhibited. See Table N - 1 for descriptive statistics. Animacy was measured using the Animacy subscale of the Godspeed Questionnaire Series (Bartneck et al., 2009b). In terms of animacy, no main effect for transparency was exhibited, $F(1, 39) = 0.76$, $p = .39$, $\omega^2 = .00$. Participants' specific animacy attribution values are available in Table N - 2. Likeability was measured using the Likeability subscale of the Godspeed Questionnaire Series (Bartneck et al., 2009b). In terms of likeability, no main effect for transparency was revealed, $F(1, 39) = 3.15$, $p = .08$, $\omega^2 = .04$. Participants' specific likeability attribution values are available in Table N - 3. Perceived Intelligence was measured using the Perceived Intelligence subscale of the Godspeed Questionnaire Series (Bartneck et al., 2009b). In terms of perceived intelligence, no main effect for transparency was revealed, $F(1, 39) = 2.30$, $p = .14$, $\omega^2 = 0.02$. Participants' specific perceived intelligence attribution values are available in Table N - 4. Perceived Safety was measured using the Perceived Safety subscale of the Godspeed Questionnaire Series (Bartneck et al., 2009b). In terms of perceived safety, no main effect for transparency was revealed, $F(1, 39) = 0.40$, $p = .53$, $\omega^2 = .00$. Participants' specific perceived safety attribution values are available in Table N - 5.

Interactions

Performance: Classification Accuracy

Participants' correct identifications were determined by the number of times the participant clicked on the correct button in response to a model or behavior on screen. The maximum number of correct identifications a participant could make, per scenario, was 28. Participants' correct identification count, and other descriptive statistics, is available in Table J - 1. Incorrect identifications are defined by participants responding to a stimulus on the screen by clicking on the wrong button. Participants, overall, made relatively few errors (see Table J - 2 for descriptive statistics). A miss is defined as a participant not clicking any button after six seconds of exposure to the stimulus. Overall, participants rarely missed identifying an event (see Table J - 3 for descriptive statistics).

In terms of correct identifications, there was an interaction between communication pattern and transparency, $F(1, 39) = 3.97$, $p = .05$, $\omega^2 = .06$. Participants' correct identification count is depicted in Figure 17, with specific values available in Table J - 1.

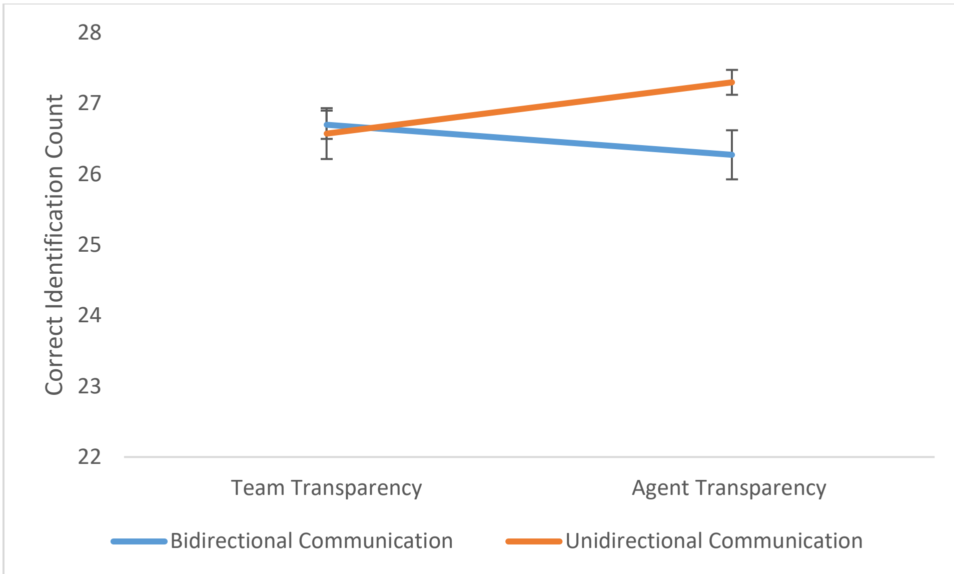


Figure 17. Correct identifications for Transparency and Communication Pattern combinations. Error bars represent standard error.

In terms of incorrect identifications, no interaction effect was found, *F(1, 39)* = 2.94, *p* = .09, ω^2 = .03. In terms of misses, no interaction effect was found, *F(1, 39)* = 3.08, *p* = .09, ω^2 = .03.

Performance: Reaction Time

Participants' reaction time was determined by the median time that participants took to select the correct answer in response to a model or behavior on screen during a scenario. In terms of reaction time, no interaction effect was found, *F(1, 39)* = 1.45, *p* = .24, ω^2 = .01. See Table J - 4 for descriptive statistics.

Situation Awareness

Situation awareness refers to the percentage of SA questions that participants answered correctly during a scenario. The score for overall situation awareness was determined by pooling participants' SA Level 1, SA Level 2, and SA Level 3 scores together and creating an average. SA Level 1 refers to the percentage of Level 1 SA questions answered correctly during a scenario. SA Level 2 refers to the percentage of Level 2 SA questions answered correctly during a scenario. SA Level 3 refers to the percentage of Level 3 SA questions answered correctly during a scenario.

In terms of overall SA, no interaction effect was found, $F(1, 39) = 0.22$, $p = .64$, $\omega^2 = .00$. In terms of SA Level 1, no interaction effect was found, $F(1, 39) = 0.86$, $p = .36$, $\omega^2 = .00$. In terms of SA Level 2, no interaction effect was found, $F(1, 39) = 0.00$, $p = 1.00$, $\omega^2 = .02$. In terms of SA Level 3, no interaction effect was found, $F(1, 39) = 0.00$, $p = 1.00$, $\omega^2 = .00$.

Overall Workload

Workload describes participants' unweighted global workload score as determined by their responses on the NASA-TLX after each scenario. Responses to each subscale were averaged together to create an estimate of overall workload, an approach which has been referred to as Raw TLX (Hart, 2006). No interaction effect was found, $F(1, 39) = 2.42$, $p =.13$, $\omega^2 = .02$. See Table L - 1 for descriptive statistics.

Trust

Trust was measured using Jian and Associates' (2000) Trust in Automated Systems survey after each scenario. IAT block was used as a between-subjects factor. A mixed-factorial ANOVA was performed to determine the effect of transparency and communication pattern on trust in the robot, and how incoming attitude toward automation influences this trust. No three-way interaction effect was found, $F(1, 38) = 0.15$, $p = .71$, $\omega^2 = .00$. No interaction effect between either IAT block and communication pattern was found, $F(1, 38) = 0.19$, $p = .66$, $\omega^2 = .00$, nor between IAT block and transparency, $F(1, 38) = 0.03$, $p = .32$, $\omega^2 = .00$. No interaction effect between communication pattern and transparency was found either, $F(1, 38) = 0.68$, $p = .42$, $\omega^2 = .00$. See Table M - 4 for descriptive statistics.

Godspeed Questionnaire Series

The Godspeed Questionnaire Series was used to determine the attitudes that participants held towards the robot with which they worked. Participants were instructed that, in each condition, they worked with a different robot, so the questionnaire series was administered after each condition. Anthropomorphism was measured using the Anthropomorphism subscale of the Godspeed Questionnaire Series (Bartneck et al., 2009b). In terms of anthropomorphism, no interaction effect was found, $F(1, 39) = 1.80$, $p =.19$, $\omega^2 = .01$. See Table N - 1 for descriptive statistics. Animacy was measured using the Animacy subscale of the Godspeed Questionnaire Series (Bartneck et al., 2009b). In terms of animacy, no interaction effect was found, $F(1, 39) = 1.38$, $p = .25$, $\omega^2 = .01$. Participants' specific animacy attribution values are available in Table N - 2. Likeability was measured using the Likeability subscale of the Godspeed Questionnaire Series

(Bartneck et al., 2009b). In terms of likeability, no interaction effect was found, $F(1, 39) = 0.08$, $p = .78$, $\omega^2 = .00$. Participants' specific likeability attribution values are available in Table N - 3. Perceived Intelligence was measured using the Perceived Intelligence subscale of the Godspeed Questionnaire Series (Bartneck et al., 2009b). In terms of perceived intelligence, no interaction effect was found, $F(1, 39) = 0.80$, $p = .38$, $\omega^2 = .00$. Participants' specific perceived intelligence attribution values are available in Table N - 4. Perceived Safety was measured using the Perceived Safety subscale of the Godspeed Questionnaire Series (Bartneck et al., 2009b). In terms of perceived safety, no interaction effect was found, $F(1, 39) = 0.26$, $p =.61$, $\omega^2 = .00$. Participants' specific perceived safety attribution values are available in Table N - 5.

CHAPTER FIVE: DISCUSSION

Prior research into transparency focused on the human operator using a robot—or other agent—to complete their task (Helldin, Ohlander, Falkman, & Riveiro, 2014; Kim & Hinds, 2006; Wright et al., 2016). In order to better deal with the direction of robot development in the military and the dynamic nature of the battlefield, this research paradigm was shifted to envelop more autonomous robots that could enable more complex forms of mixed-initiative interaction (Chen et al., 2018; Defense Science Board, 2016; U.S. Army, 2017). This approach, however, has been largely theoretical until now. Generally, this study used the previously established theoretical approach to explore how humans and robots can communicate in order to build shared understandings. Specifically, this study sought to examine how transparency type and human-robot communication pattern could influence participant SA, trust in a robot, subjective workload, performance, and attitude toward the robot. Overall, participants did not seem to be affected by the type of transparency to which they were exposed. Instead, communication pattern seemed to spark differences. Each outcome will be examined, then larger takeaways will be discussed.

Communication Pattern

Performance: Classification Accuracy

Participants' performance can be thought of as classification accuracy and reaction time. Classification accuracy is divided into three major components, for the purposes of this study: correct identifications, incorrect identifications, and misses. Correct identification, essentially the participant correctly identifying an event, is a useful counterpart to participant errors. Both incorrect identifications and misses can be grouped as errors, the former as errors of commission—the participant doing the wrong thing—and the latter as errors of omission—the participant failing to do the correct thing.

When participants worked with a querying robot, they made fewer correct classifications and missed more classifications than when they worked with a non-querying robot. The increased errors, specifically misses, in conditions where the robot queried the participant, partially supports hypothesis 1.1. The act of answering a query using the visual interface added to the participants' taskload, which was expected to split participants' attention. Furthermore, the participants missed classifying events rather than incorrectly classifying events, suggesting the issue wasn't misunderstanding so much as it was difficulty doing necessary tasks in the required time. While significant, however, the effect sizes for the difference in correct identifications (ω^2 = 0.04) and misses (ω^2 = 0.03) are small to medium. The additional task, answering queries, affected performance, but did not affect perceived workload. Altogether, these findings suggest that the addition of a query-answering task affected participants' performance in an identification task, but not so much that it would lead to an increase in perceived workload for the overall cordon and search-like task. Furthermore, supporting verbal response to the robot may actually obviate this issue entirely. Multiple resource theory states that people process information along several dimensions, including both visual and auditory modalities (Wickens, 2008). When participants have to commit concurrent tasks, like they do in this study, changing the dimension of one of those tasks can reduce interference and extend mental limitations (Lakhmani et al., 2016; Wickens, 2002). By changing the response from a button click to a vocal response, participants would spend less time physical responding to the system.

Performance: Reaction Time

Participants' performance can also be measured in terms of reaction time. It was expected that participants would take longer to identify relevant stimuli when they worked with a querying agent than when they didn't (hypothesis 1.1). Contrary to expectations, there was no difference in reaction time, regardless of communication pattern. However, if participants take too long to classify the event on the screen, it is considered a miss. Given the effect that communication pattern had on correct identification and misses, as well as the dearth of effect on incorrect identifications, the case can be made that participants' decision making was delayed enough that their responses could be categorized as misses.

Situation Awareness

In each condition, participants received a number of situation awareness probes. These probes were used to assess the participants' awareness of the simulated environment, including not only specific events, but also rationales and projected outcomes relevant to both the human and robot team members. It was expected that participants who were working with a querying robot would correctly answer more of these SA probes than participants who worked with a non-querying robot (hypothesis 1.2). Participants, however, correctly answered roughly the same number of questions regardless of communication pattern, contrary to the expectations set by hypothesis 1.2. These findings suggest that being asked about one's priorities won't make someone more likely to pay more attention to the factors that would influence one's priorities. Greater robot autonomy was expected to increase human's engagement with the robot (Morrow & Fiore, 2012), but that engagement did not translate into greater situation awareness.

Overall Workload

After participants completed each scenario, they were given the NASA-TLX and asked to rate their subjective workload during that scenario. As stated in hypothesis 1.2, it was expected that participants would report higher workload for scenarios where the robot queried them. In fact, there was no difference in reported workload for participants. Curiously, while communication pattern did not seem to affect subjective workload, it did affect performance. While participants did not perceive greater workload when they worked with a querying robot, they did classify fewer events correctly and miss more identifications than when they worked with a non-querying agent. This finding suggests that either communication pattern did have an effect, but not one strong enough for the participants to consciously detect, or communication pattern had an effect on part of the task, but that effect vanished when the rest of the task was taken into account.

Trust

Participants were asked to complete trust surveys after completing a scenario. Participants reported similar trust scores, regardless of communication pattern, which contradicted hypothesis 1.2. Trust is based off of the knowledge that the trustee, i.e. the robot, can accomplish the desired goal, i.e. keeping intruders out of the building (Lee & See, 2004). Schaefer and associates surveyed the literature to find the factors that can affect humans' trust in a robot; relevant robot-specific factors include the robot's behavior, feedback, and level of automation (Schaefer, Chen, Szalma, & Hancock, 2016). The similar responses to both querying and non-querying agents suggest that: queries were not considered a notably different behavior than an absence of queries; a querying robot did not convey a different level of automation than a non-querying robot; and the amount of feedback provided by a robot pushing a binary-choice query was not dissimilar to no robot query at all.

Godspeed Questionnaire Series

The Godspeed Questionnaire Series describes a series of attitudes that participants often have towards a robot with which they interact. In hypothesis 1.2, participants were expected to react to the robot on all five categories—i.e. Anthropomorphism, Animacy, Likeability, Perceived Intelligence, and Perceived Safety. No experimental manipulation affected participants' attitude towards the robot in terms of anthropomorphism or perceived safety. However, when participants worked with a querying robot, they found it to be more animate, likeable, and intelligent than its non-querying counterpart, partially supporting hypothesis 1.2. These findings suggest that the more explicitly interactive element of answering queries affected participants' attitudes towards the robot.

In the field of social robotics, one study—featuring a robot that matched the facial expressions of its partner and a human playing a game then helping it label objects in pictures—reported similar findings. The participants who worked with the robot when it explicitly asked about their emotional state (in order to match its expression with the human's mood) perceived it as more anthropomorphic and more animate than the participants who worked with the robot when it neither queried the human nor explicitly communicated its matching mood (Kühnlenz et al., 2013). Unlike the current study, Kühnlenz and associates (2013) used a robot with a human-like face, which may explain the similarity in animacy and dissimilarity in anthropomorphism.

Furthermore, in a study where humans were charged with teaching concepts to a socially guided machine-learning robot, they reported that they perceived the robot to be more intelligent and more enjoyable to teach when it would query the human during the learning task (Cakmak, Chao, & Thomaz, 2010). In these studies, as in the current study, participants saw the more interactive robots as more animate, likeable, and intelligent, than their more passive counterparts.

Type of Transparency

Performance: Classification Accuracy

Type of transparency alone did not affect participants' performance on the classification task, which conflicts with the expectations set by hypothesis 2.1. Furthermore, while it was expected that transparency type could mitigate the error rate that would occur from the added taskload of answering queries, transparency type did not seem to have that effect, instead acting as more of a distraction in some circumstances, as discussed above.

Performance: Reaction Time

It was expected that participants would take longer to classify events when they worked with an agent that presented both transparency modules (hypothesis 2.1). This expectation was not met. Instead, no significant difference was found between the agent transparency condition and the team transparency condition. The similar reaction time between transparency types suggest that the two interface options were considered similarly. This similar consideration may have been due to either cognitive grouping of transparency modules or may have been due participant neglect of said modules. While the participant could use the team transparency module to help them identify the target, it is likely that they, instead, looked at the target directly and made a judgment based off of the mental model established through training. Given the low number of incorrect identifications (see Table J-2), their target identification was not hampered by the reliance of their mental models. Either way, the effect of the manipulation was minimal.

Situation Awareness

It was also expected that when participants were exposed to both types of transparency, they would exhibit greater SA than when they were only exposed to agent transparency (hypothesis 2.2). Contrary to expectations, participants exhibited an equal amount of SA, regardless of transparency type. These findings suggest that participants were either only intermittently focusing on the team transparency modules, or that they focused only on the agent transparency module. All conditions include the agent transparency module, so participants mental models may have focused on gaining information from features that were consistently available, such as the agent transparency module or targets in the simulated environment. This occurrence would not only explain why participants' overall SA scores did not differ, regardless of transparency type, but it would also explain why participants achieved the scores they did, despite the fact that the transparency modules would provide the answer to between half and two-thirds of the SA questions. When questions were considered by SA level, no difference in SA was found regardless of communication pattern. Overall, participants answered fewer Level 3 SA questions correctly than Level 1 or Level 2 questions, but that result is not as surprising, given the difficulty people often have with projecting future outcomes (Endsley & Jones, 2016). Transparency type did not significantly affect participants' SA, regardless of level, but the size of the effect in both levels 2 and 3 ($\omega^2 = .05$) approached medium. This information, coupled with greater Level 2 and 3 SA when participants had the team transparency module available, suggests that further research and development of a team transparency module may yield fruit.

Overall Workload

Hypothesis 2.2 stated the expectation that participants would report higher workload for scenarios where the robot displayed both transparency modules. However, the results defied expectation and participants did not report a significant difference in workload, regardless of transparency type. While transparency type did not influence perceived workload, transparency type did influence performance, albeit as part of an interaction. Presumably, participants perceived the second module. In terms of information quantity, the team transparency condition added one module, comprised of three spaces, which could be populated from a sample of nine icons. At any time, participants in a team transparency condition perceived three additional icons, which was a small increase in the amount of information on screen. One study, focusing on information quantity in computer-based procedures for nuclear power plants, suggests that a difference in information quantity (below, at, or above maximum channel capacity) results in a difference in participant workload, as expressed by the NASA-TLX (Hsieh, Chiu, & Hwang, 2015).

The similarity in perceived workload between agent transparency and team transparency conditions suggest that the amount of information that was displayed in one condition was not considered noticeably different than the amount of information that was displayed in the other. Previous studies using at-a-glance modules to explain an agent's decision making process found that participants did not report differences in workload, despite varying the number of icons used, or even adding a secondary module to provide more in-depth information (Lakhmani, Chen, Wright, Selkowitz, & Schwartz, in prep; Wright, Chen, Lakhmani, & Selkowitz, in press). This result may be a result of the second module not reaching a noticeable difference threshold, as described above, or participants chunking both module together. Chunking, the partitioning of knowledge into units, can consist of the same concepts, but from different perspectives—i.e. the agent's POV and the agent's model of the human's POV (Cooke et al., 2000). In this case, reading both transparency modules did not cognitively encumber participants because they were both chunked together into a larger whole.

Trust

Defying the expectations of hypothesis 2.2, participants reported a similar amount of trust, regardless of the transparency type they witnessed. Previous research using at-a-glance transparency modules—similar to the agent transparency condition—found that agents that provide information corresponding to all three SAT levels are more trusted than those that support fewer levels (Selkowitz, Lakhmani, & Chen, 2017a). Based on those findings, the current study's at-a-glance module was set to support all three SAT levels. A different study focused on adding a secondary module, describing the underlying factors that led to the agent's decision (Wright et al., in press). This additional information did not facilitate greater trust in the agent. These three studies, all of which used an at-a-glance module to facilitate transparent interaction with a vehicular agent, suggest that a baseline at-a-glance transparency module that addresses all three levels of SAT is most trustworthy, but additional information about the innermost workings of a robot provide diminishing returns, with regards to trust.

Godspeed Questionnaire Series

Unlike communication pattern, transparency type did not affect participants' attitude towards the robot, which was contrary to the expectations set up in hypothesis 2.2. The information provided by the secondary transparency module may have been considered unnecessary—either due to the nature of the participants' tasks or the complexity of the task—or was only considered intermittently. Wright and associates (in press) found something similar when comparing transparency modules that described the robot's decision making process at either a surface level or at a more in-depth level. Participants had similar attitudes towards robots with both a simple, at-a-glance modules and a module providing more in-depth information, which Wright and associates (in press) attributed to the simplicity of the human-robot task. Essentially, participants did not need the in-depth decision making information in order to complete the task, rendering it superfluous (Wright et al., in press). While the task used in the current study was more complex than that used in Wright et al (in press), the task may not have specifically required a continuous updated understanding of the robot's understanding of their own decision making process. Consequently, the interface feature, which participants may have only intermittently observed, would thus have limited effect on the participants' attitudes toward the robot.

Interactions

Performance: Classification Accuracy

While there was a significant interaction between communication pattern and transparency type on participants' correct identification of targets, it contradicted the expectations set about by hypothesis 3.1. In the agent transparency condition, participants identified more targets correctly when they worked with a robot that communicated with them unidirectionally than when they worked with its transactionally communicating counterpart. There was no difference in the number of correct identifications when participants worked with a robot that displayed the team transparency at-a-glance module. This finding suggests that the additional interface module in the team transparency condition added a cost in time or cognitive resources, similar to the communication overhead seen in human communication, such that unidirectional communication no longer conferred an advantage in correct identifications (MacMillan et al., 2004).

These performance findings suggest that the team transparency module conveyed information to the participants and that information had an effect on participants. However, given the workload findings, this effect wasn't noticed by the participants. This suggests that the effect of the team transparency module was slight, or that it was only observed intermittently. While the participants' SA did not did not differ significantly when presented with the team transparency module, the moderate effect size may support the idea of intermittent observation of this module. During training, participants were shown the possible robot and human states, which were constrained, given the short time available to train participants. Consequently, participants may have established a mental model of the robot's understanding of their own decision making process, only occasionally updating it, using the team transparency module, when it was available.

Performance: Reaction Time

Given the minimal effect that communication pattern manipulations and transparency type manipulations had on participant reaction time, the lack of interaction effect (as described in hypothesis 3.1), was unsurprising.

Overall Workload

When participants worked with an agent that didn't query and only provided the agent transparency module, they did not report a higher workload than when they worked with other agents, despite expectations set by hypothesis 3.1, suggesting that participants were not mentally keeping track of this information to an extent that it produced a notable cognitive load. If participants were not keeping track of the information, then visualizing that information does not save any cognitive effort. The subjective workload results differ from the participants' correct identification results, where the addition of the team transparency information added a communication overhead. This difference suggests that team transparency had an effect on performance, but not one that was noticed by the participants.

Trust

Participants, before learning about the tasks they would be asked to complete, completed an implicit attitude test focusing on their feelings towards humans and machines. Two iterations of this test were given in order to avoid systemic error. Unfortunately, unlike a previous IAT comparing humans and machines (Merritt et al., 2012), participants who received one iteration scored significantly differently than those that received the other. While an order effect in an IAT is not unknown (Nosek et al., 2005), it also prevented the use of a repeated measures ANCOVA. Rather than using IAT score as a covariate, the specific scores for both iterations were standardized and merged so that there was one group instead of two. Those scores were blocked into groups and used as a between subjects individual difference factor.

Analysis of post-scenario trust and implicit trust in automation showed that there was no interaction between incoming, implicit trust in machines and post-task trust in automation, so this finding defies the expectations of hypotheses 1.2, 2.2, and 3.1. A possible explanation for this outcome may, in fact, be due to the efforts to facilitate transparent human-robot interaction. Merritt and associates (2012) suggest that implicit attitudes toward automation were more predictive of trust when the automation's performance was ambiguous. The addition of the at-a-glance transparency modules are explicitly meant to combat ambiguity, by providing relevant information that a human teammate might need. The lack of ambiguity, due to the presence of transparency modules, may have weakened the effect that implicit attitudes may have had.

Communication pattern and transparency type did not affect participants trust and neither did the interaction between these two factors. Contrary to hypothesis 3.1, the non-querying agent only displaying the agent transparency module was not considered less trustworthy than any of its counterparts. Since a non-querying agent displaying only the agent transparency module was considered equally trustworthy as its counterparts, this suggests that the factors under consideration did not affect participant trust enough to be noticeable, or that these factors were counteracted by a stronger factor, like reliability (Schaefer et al., 2016).

Situation Awareness

Given that communication pattern and transparency type did not significantly affect participants' situation awareness, the failure to support hypothesis 3.2 was unsurprising. Altogether, these findings suggest that, while hypotheses 1.2, 2.2, and 3.2 were not supported, when it comes to SA, providing more information about the robot's understanding of its human teammate's decision making process may prove to be useful, depending on the context of the task and the way it is displayed.

Godspeed Questionnaire Series

Despite communication pattern influencing participants' attitudes towards the robot, no interaction effect between type of transparency and communication pattern was found, contradicting expectations set up by hypothesis 3.3.

CHAPTER SIX: CONCLUSIONS

What are the Implications of Communication Pattern

In the context of a human-robot team, where a human is individually tasked with identifying stimuli while sharing a cordon-and-search-like task with a robot, the robot's communication pattern had the largest effect on their human teammates. Two major implications can be reached from these findings. The first pertains to human performance on a secondary task while communicating with a robot. The second relates to humans' attitudes towards robots that utilize different communication patterns.

A decrease in correct identifications and an increase in misses suggests that human-robot interaction, using a robot-push and robot-pull communication pattern, has a cost, which parallels those seen in in human teamwork and automation use (Williams, Briggs, & Scheutz, 2015). In human teamwork, the exchange of information is often needed to accomplish the desired goals of the team, but this exchange necessitates an investment of cognitive effort and time, i.e. a communication overhead (MacMillan et al., 2004). When interfacing with automated systems, humans can direct their attention to relevant parts of the interface, but if they try to commit multiple tasks simultaneously, then their divided attention may result in reduced performance in those tasks (Derryberry & Reed, 2002; Wickens, 2002). In this experiment, where participants communicated with a robotic teammate by splitting their attention between a correct identification task and clicking on a box on a separate screen, participants' performance indicated that they may have been paying a communication overhead. Consequently, the approach used to facilitate transactional communication in this study may be preferable in situations where reduced performance or increased miss rate has minimal repercussions, such as when robots are being used for entertainment or in situations where humans and robots are planning future outcomes. These repercussions may be mitigated, however, through the use of a multimodal human-robot interface.

A robot-push, robot-pull communication pattern also resulted in participants seeing the robot as more animate, intelligent, and likeable. The attitudes that human teammates have towards their robotic teammates can influence their behavior towards those robots (de Graaf & Allouch, 2013; Schaefer et al., 2016). Animacy is related to human attribution of beliefs, intentions, and desires onto others, so a robot that is seen as more animate may be observed by humans with the expectation of intentionality (Jones & Schmidlin, 2011). This expectation could yield an opportunity for communication that a robot seen as less animate wouldn't have. The increased likeability of a querying robot also has implications for robots that require input from humans. The social complexity and the use of reciprocity can induce people to like the robot more, possibly leading to increased likelihood of answering more questions (Sandoval, 2016; Vouloutsi, Grechuta, Lallée, & Verschure, 2014). Finally, if a robot is perceived to be more intelligent, then people tend to go along with its actions (Bartneck et al., 2009b). In a mixed-initiative human-robot interaction, getting humans to buy in to the robot's agency is key, so if querying can increase perceived intelligence, it may also subsequently increase the likelihood that humans will go along with the robot's actions.

Finally, these findings have implications for how we see robots, in terms of levels of automation. Parasuraman and associates (2000) detailed ten levels of automation whereby the human and a system interact, ranging from full human autonomy to full system autonomy. The interactivity established through the communication patterns used in this study, however, suggests that the interaction needed to support transactional human-robot communication lies in the space between level 8 (informs the human only if asked) and level 9 (informs the human only if it, the computer, decides to). These levels assume a human-push or human-pull pattern, but insufficiently describe a human-robot interaction where robots use a robot-push/robot-pull pattern—a communication pattern used in this study. A mixed-initiative approach, one that falls between these two levels, must be used in order to explore the interactions between humans and robots with extensive autonomous capabilities.

What are the Implications of Transparency

Unlike communication pattern, no major difference was found with respect to transparency alone. Revealing the robot's understanding of the participants' decision making process affected the human's response to the robot in conjunction with communication pattern. Coupled with the moderate effect size of transparency type in participants' non-significant Level 2 and Level 3 SA scores, this response suggests that participants made minor or intermittent use of the secondary module in the team transparency conditions, but that use still engaged participants enough to invoke a communication overhead.

Presumably, participants established a mental model of the robot's mental model of them, then only rarely checked afterwards if that model was accurate. For this study, the robot was designed not to incorrectly characterize what the decision making process of the human teammate should be, so acknowledging or correcting error was never part of the participants' tasks. Additionally, the team transparency module could not be used to prevent failure of the shared task—keeping intruders outside the cordoned building—as the study used a canned simulation paradigm. Participants may not have needed to regularly observe the secondary module, except for the situation awareness probes, which came without warning and blacked out the screen so participants could not check after the fact. Unlike in supervisory control tasks, where understanding the internal aspects of the robot is part of the human's task, the team transparency module is meant to inform human team members of the state of the team. Given that they know their own status, they would not check the robot's understanding of their own status unless that knowledge was needed to accomplish their own task or prevent failure of the shared task. The implications for these findings suggest that a consistently displayed transparency module used to create a shared understanding of the state of the team may does not necessarily result in consistent observation. This suggests that the module needs to be more instrumental to the task at hand or may need to be emphasized when needed, either by the robot or the human.

This study's findings also have implications for the dynamic SAT model and its implementation. The traditional SAT module suggests that robots need to provide certain categories of information to their human operators in order to support the human's awareness of the robot and its place in the larger decision-space (Chen et al., 2014). The dynamic SAT model, however, encompasses both human and robot team members' informational needs (Chen et al., 2018). While the team transparency condition conveyed the transparency information that humans and robots were expected to need, the team transparency module was only used intermittently and engendered a communication overhead when coupled with a robot query. This suggests that the loop of information (in this instance, centered around the robot pushing information to and pulling from a human) may in fact need to be mutually reinforced through multiple channels, more closely mimicking Barnlund's (1970) model of communication.

Limitations of the Study and Areas for Future Study

Given the nature of the tasks and the challenge of simulating teamwork, a number of limitations must be discussed. First, and foremost, is that the tasks being simulated are of a military context, but were given to a civilian population. In order to compensate for this mismatch, participants were given a simplified version of the military task and were trained to use the system. These participants did not have the expertise that soldiers have, pertaining to the task at hand and to the larger context of military operations. These participants, however, were more readily available than soldiers. Further, while the simplified tasks allowed for greater experimental control, they also came at the cost of generalizability. Cordon-and-search tasks are more complicated than the simplified tasks that were presented to the participants, involving more teammates, more complex interactions with the actors in the environment, and more stimuli than were available in the simplified task. Future studies could focus on more complex environments that more closely adhere to the actual cordon-and-search task, even if it is still simplified. Furthermore, the increased complexity could force users to use the transparency modules more consistently, which was an issue that stymied previous efforts at exploring the effects of at-a-glance transparency modules (Wright et al., in press).

Additionally, the collaborative task used in this study focused on communication and maintaining shared understanding, with some interactivity. By altering the content or frequency rate of robots' queries, future studies could find different effects and thus further define the scope of these variables' effects. Furthermore, the approach used here showed that transparency type and communication pattern affected participants, but a different task, one that featured human-robot coordination, may yield different effects than those found in the current study. Future studies can use more advanced technology, or a confederate in a Wizard of Oz design, to explore different kinds of human-robot interaction and how both transparency type and communication pattern can be used to improve that interaction (Riek, 2012).

Furthermore, this study only explored the effects of two communication patterns, robot-push alone and robot-push coupled with robot-pull. Future studies could examine the effects of different patterns and explore how these different patterns affect a human-robot team's performance and relationship. Additional humans and robots can be included, expanding the makeup of teams that can be discussed in this exploration of human-robot interaction.

Another issue is the use of solely visual modalities. As previously discussed, the performance decrement found as a result of the robot's queries may have been reduced or even nullified if the interface had put the querying interface closer to the area where the participants classified stimuli, if the participants used a tablet instead of a second monitor, or if the robot allowed the participant to respond verbally. Further studies could explore different modalities of interaction, on both the human and robot sides, and determine how each of these different approaches affects participants' behavior and response.

Overall, the goal of this research is to improve human-robot interaction through manipulating both the communication patterns available to the participant and the way transparency is supported in a human-robot interface. The findings of this study suggest that people working with robots respond positively to greater interactivity, when it comes to subjective attitude. However, this interactivity must be carefully implemented, given how a solely visual presentation of queries led to performance decrements. Furthermore, as the transparency findings suggest, consistent display of information does not correspond with a consistent observation of said information. Even when that information was directly needed to for one of their tasks, participants still only intermittently observed the second transparency module. Consequently, future researchers and designers should determine how best to draw attention to this information and when to do so. In the end, exploring the effects of communication patterns and transparency is only the beginning of a larger exploration of human-robot communication.

APPENDIX A: **IRB APPROVAL LETTER**

University of Central Florida Institutional Review Board
Office of Research & Commercialization
12201 Research Parkway, Suite 501
Orlando, Florida 32826-3246
Telephone: 407-823-2901 or 407-882-2276
www.research.ucf.edu/compliance/irb.html

Approval of Human Research

From: **UCF Institutional Review Board #1**
FWA00000351, IRB00001138

To: **Shan G Lakhmani** and Co-PI **Daniel J Barber**

Date: **October 31, 2017**

Dear Researcher:

On 10/31/2017 the IRB approved the following human participant research until 10/30/2018 inclusive:

Type of Review:	UCF Initial Review Submission Form Expedited Review Category #7
Project Title:	Approaches to Communication and Transparency in Human-Robot Teams
Investigator:	Shan G Lakhmani
IRB Number:	SBE-17-13419
Funding Agency:	Army Research Laboratory(ARL)
Grant Title:	This research study is being paid for by the Army Research Lab, part of the Department of Defense under Cooperative Agreement W911NF-14-02-0012.
Research ID:	1056451

The scientific merit of the research was considered during the IRB review. The Continuing Review Application must be submitted 30days prior to the expiration date for studies that were previously expedited, and 60 days prior to the expiration date for research that was previously reviewed at a convened meeting. Do not make changes to the study (i.e., protocol, methodology, consent form, personnel, site, etc.) before obtaining IRB approval. A Modification Form **cannot** be used to extend the approval period of a study. All forms may be completed and submitted online at https://iris.research.ucf.edu .

If continuing review approval is not granted before the expiration date of 10/30/2018, approval of this research expires on that date. When you have completed your research, please submit a Study Closure request in iRIS so that IRB records will be accurate.

Use of the approved, stamped consent document(s) is required. The new form supersedes all previous versions, which are now invalid for further use. Only approved investigators (or other approved key study personnel) may solicit consent for research participation. Participants or their representatives must receive a signed and dated copy of the consent form(s).

All data, including signed consent forms if applicable, must be retained and secured per protocol for a minimum of five years (six if HIPAA applies) past the completion of this research. Any links to the identification of participants should be maintained and secured per protocol. Additional requirements may be imposed by your funding agency, your department, or other entities. Access to data is limited to authorized individuals listed as key study personnel.

In the conduct of this research, you are responsible to follow the requirements of the Investigator Manual.

On behalf of Sophia Dziegielewski, Ph.D., L.C.S.W., UCF IRB Chair, this letter is signed by:

Signature applied by Jennifer Neal-Jimenez on 10/31/2017 04:01:43 PM EDT

Designated Reviewer

APPENDIX B: **DEMOGRAPHIC QUESTIONNAIRE**

Demographic Questionnaire

Date: ________________Participant ID: _________

1. General Information

Age: _____ Gender: _____ Handedness: _______

a. Do you have any of the following (Circle all that applies):

Astigmatism Near-sightedness Far-sightedness None Other (explain):___________

b. Do you have corrected vision (Circle one)? None Glasses Contact Lenses
If so, are you wearing them today? Yes No

c. Do you have any type of color blindness/color vision deficiency? YES NO

d. Are you in your good/ comfortable state of health physically? YES NO

e. What is your native language? ________________

f. How many hours did you sleep last night? ______ hours

2. Military Experience

a. Do you have prior military service? YES NO If Yes, how many years __________

b. Do you have any experience with Cordon and Search operations? YES NO

3. Educational Data

a. What is your highest level of education received? Select one.
____ GED
____ High School
____ Some College
____ Associates or Technical Degree
____ Bachelor's Degree
____ M.S/M.A
____ Ph.D or other doctorate
Other: ________________________

b. What subject is your degree in (for example, Engineering)? ___________________

4. Computer Experience

a. How many years have you been using a computer? _______________

b. On average, how many hours per week do you currently use a computer?
_____ hours per week

c. For each of the following questions, circle the response that best describes how often you:

Use a mouse	Never	Rarely	Once every few months	Monthly	Weekly	Daily
Use a joystick	Never	Rarely	Once every few months	Monthly	Weekly	Daily
Use a touch screen	Never	Rarely	Once every few months	Monthly	Weekly	Daily

Use icon-based programs/software	Never	Rarely	Once every few months	Monthly	Weekly	Daily
Use programs/software with pull-down menus	Never	Rarely	Once every few months	Monthly	Weekly	Daily
Use a graphics/drawing features in software packages	Never	Rarely	Once every few months	Monthly	Weekly	Daily
Use E-Mail?	Never	Rarely	Once every few months	Monthly	Weekly	Daily
Operate a radio controlled vehicle (car, boat, or plane)	Never	Rarely	Once every few months	Monthly	Weekly	Daily
Play computer/video games	Never	Rarely	Once every few months	Monthly	Weekly	Daily

d. Which of the following best describes your expertise with computer? (select one)

______ Novice
______ Good with one type of software package (such as word processing or slides)
______ Good with several software packages
______ Can program in one language and use several software packages
______ Can program in several languages and use several software packages

5. Video Game Experience

e. On average, how many hours per week do you currently play video games?
_____ hours per week

f. Which **type of video game** do you play most often?

____Action-adventure
____First person shooters
____Military-based
____Mobile/cellphone games
____Multiplayer online gaming
____Role playing
____Serious games/Educational
____Simulation
____Strategy
____Sports
____Other, please indicate which one: ____________________________

g. List your 3 most recent favorite game titles and indicate your experience with each game (circle one)

____________________________	None	Very little	Average	High	Expert
____________________________	None	Very little	Average	High	Expert
____________________________	None	Very little	Average	High	Expert

6. Robotics Experience

a. Have you any experience with **military robots**? ___Yes ___No

b. If you answered **YES** to question **6.a**, what type of robots and for what purpose?

Type Purpose

___________________ ____

___________________ ____

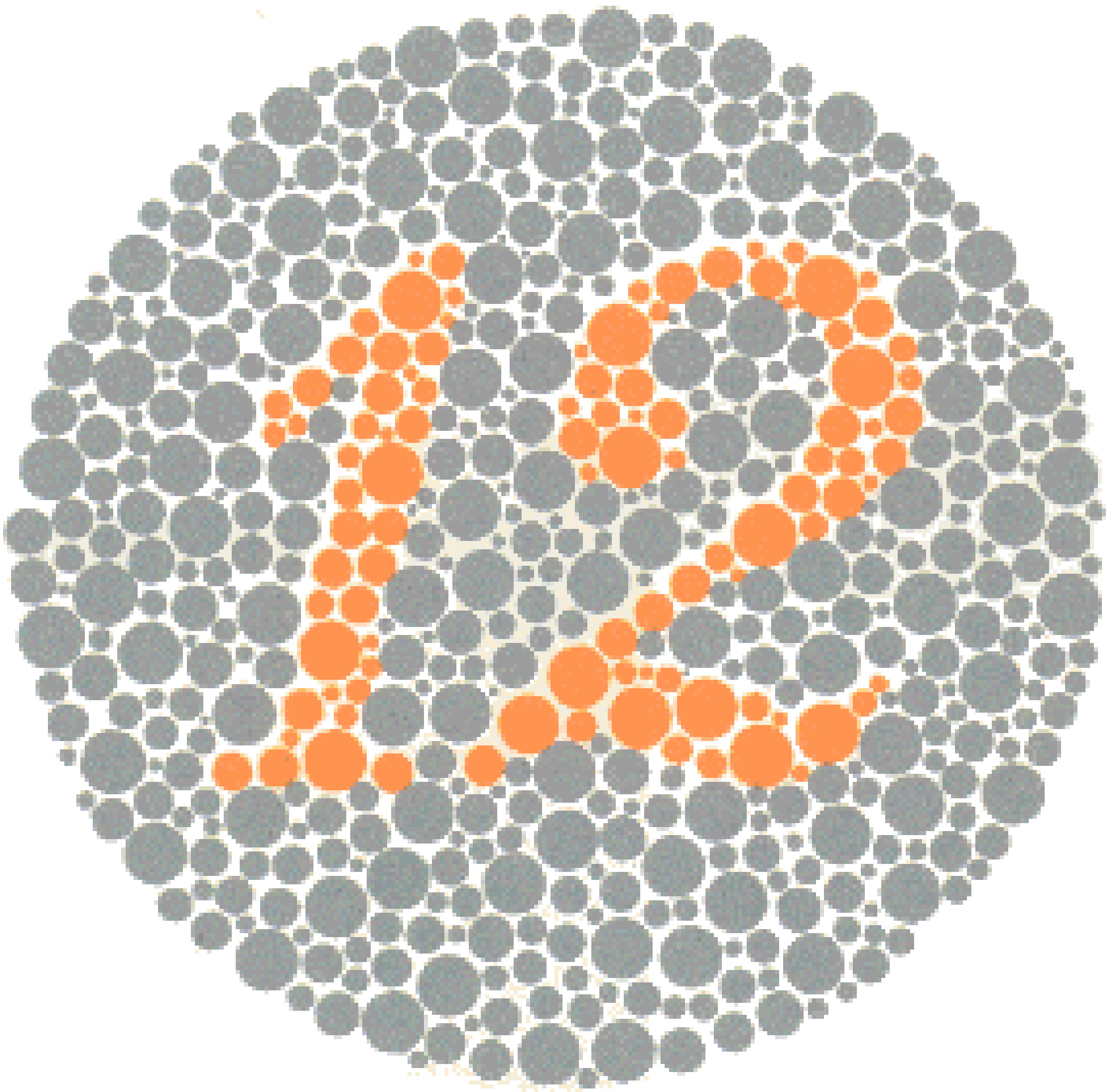
c. Please indicate how you would rate your level of experience with **any robots:**

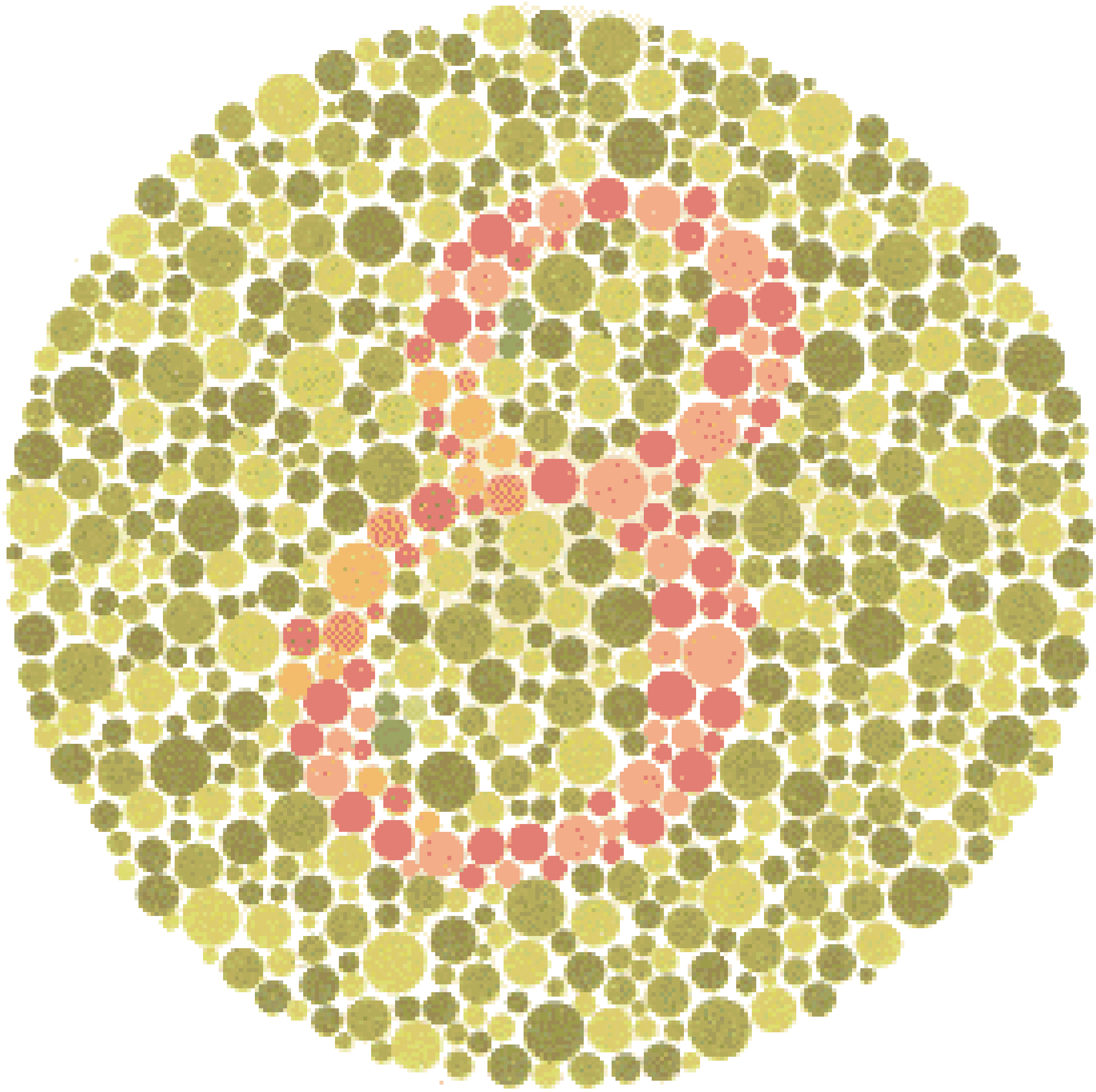
Not at all familiar	Somewhat familiar	Moderately familiar	Above moderately familiar	Highly familiar	Very highly familiar

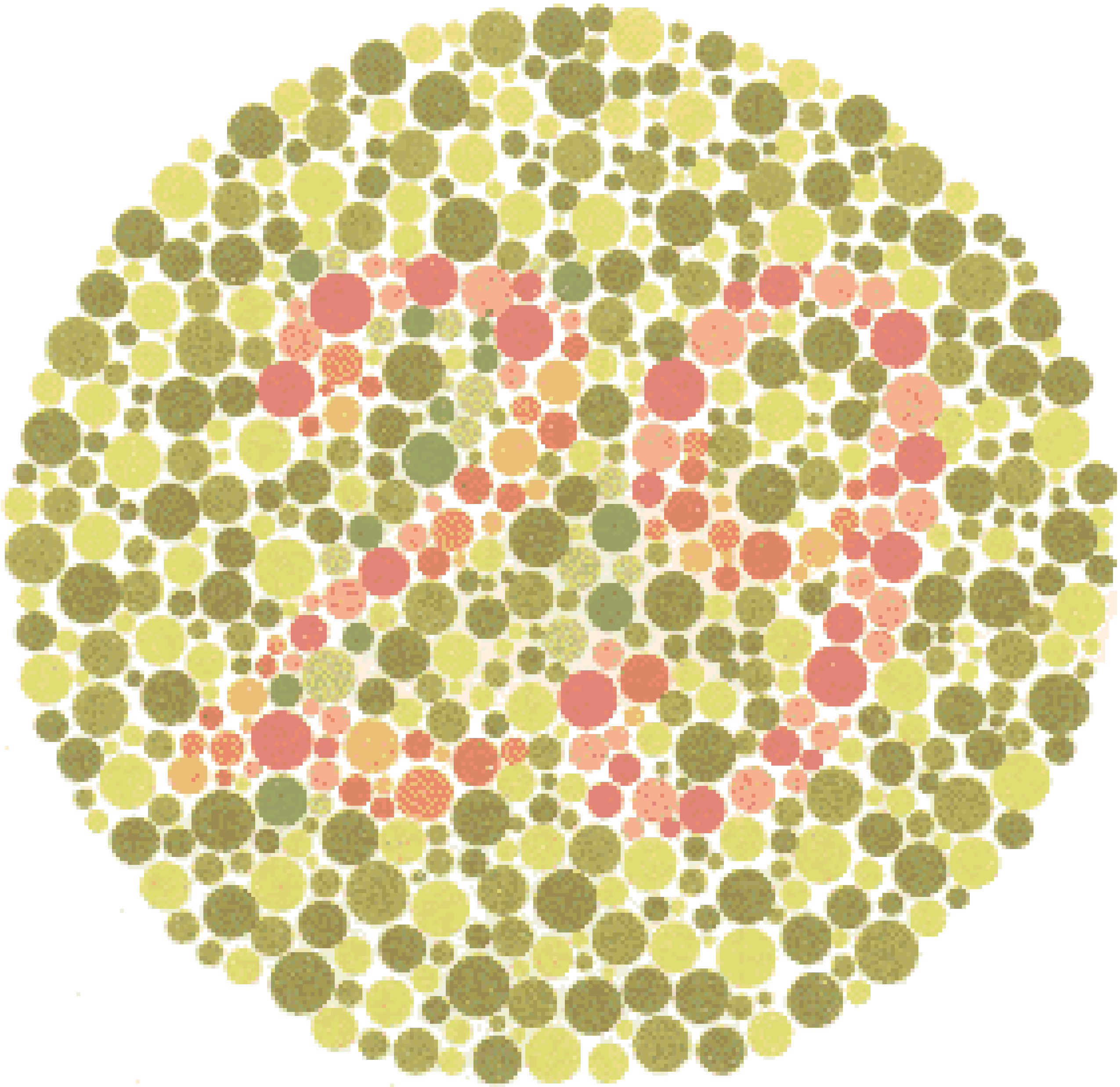
d. Please indicate how you would rate your level of knowledge regarding r**obotics technology (e.g. pack bot, big dog, talon, AIBO etc.):**

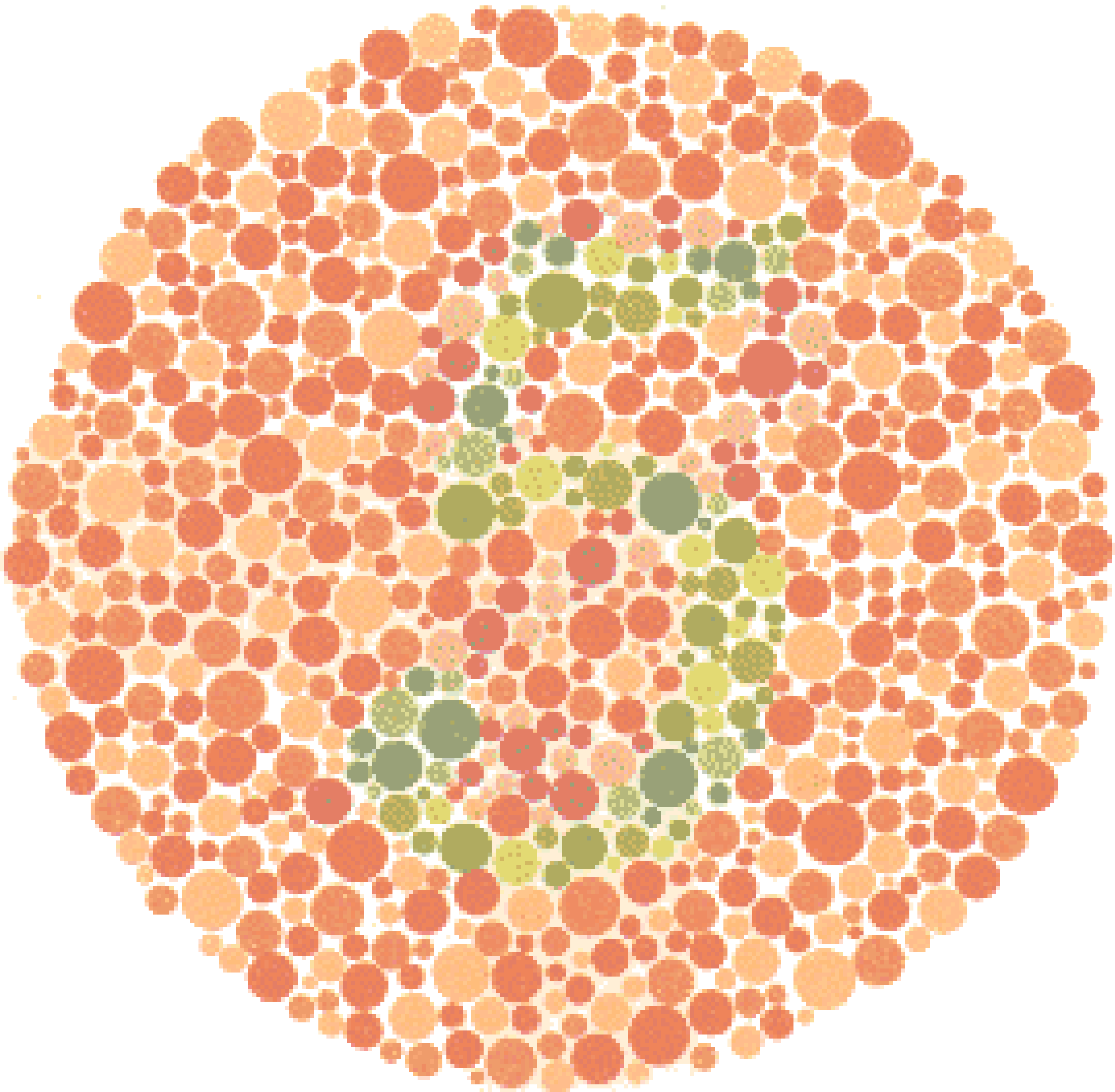
Not at all familiar	Somewhat familiar	Moderately familiar	Above moderately familiar	Highly familiar	Very highly familiar

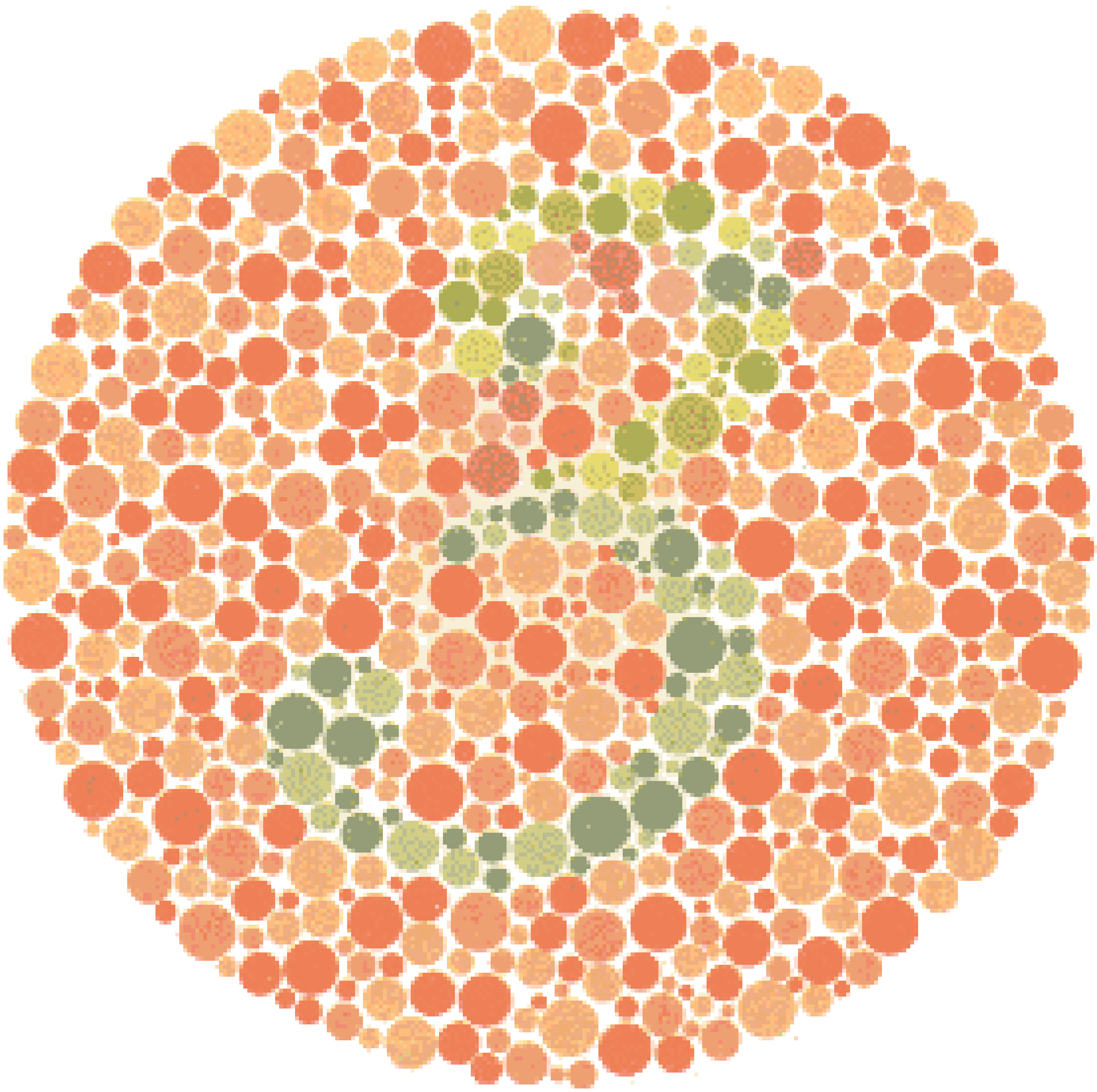
APPENDIX C: **ISHIHARA COLOR VISION TEST PLATES**

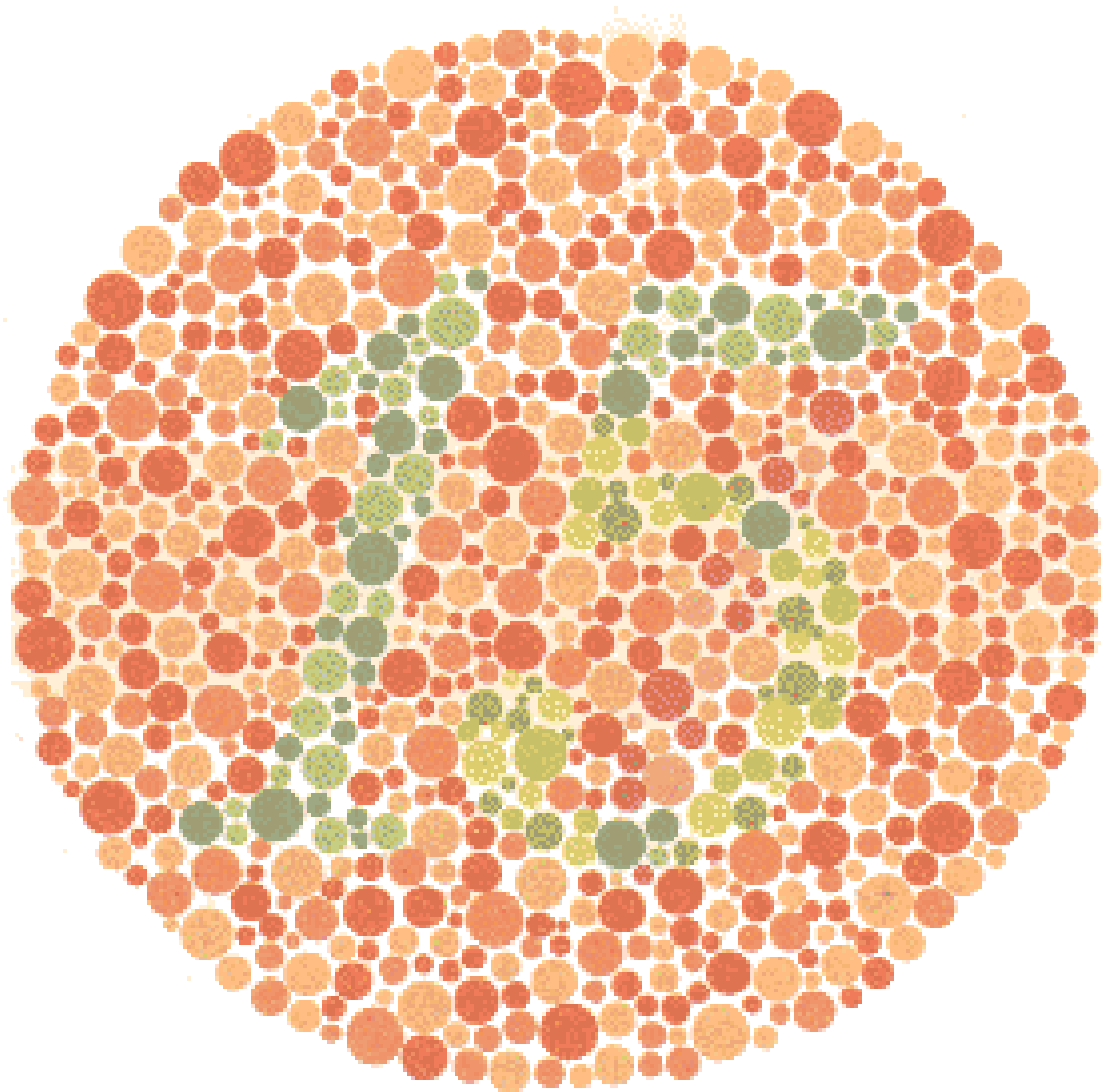


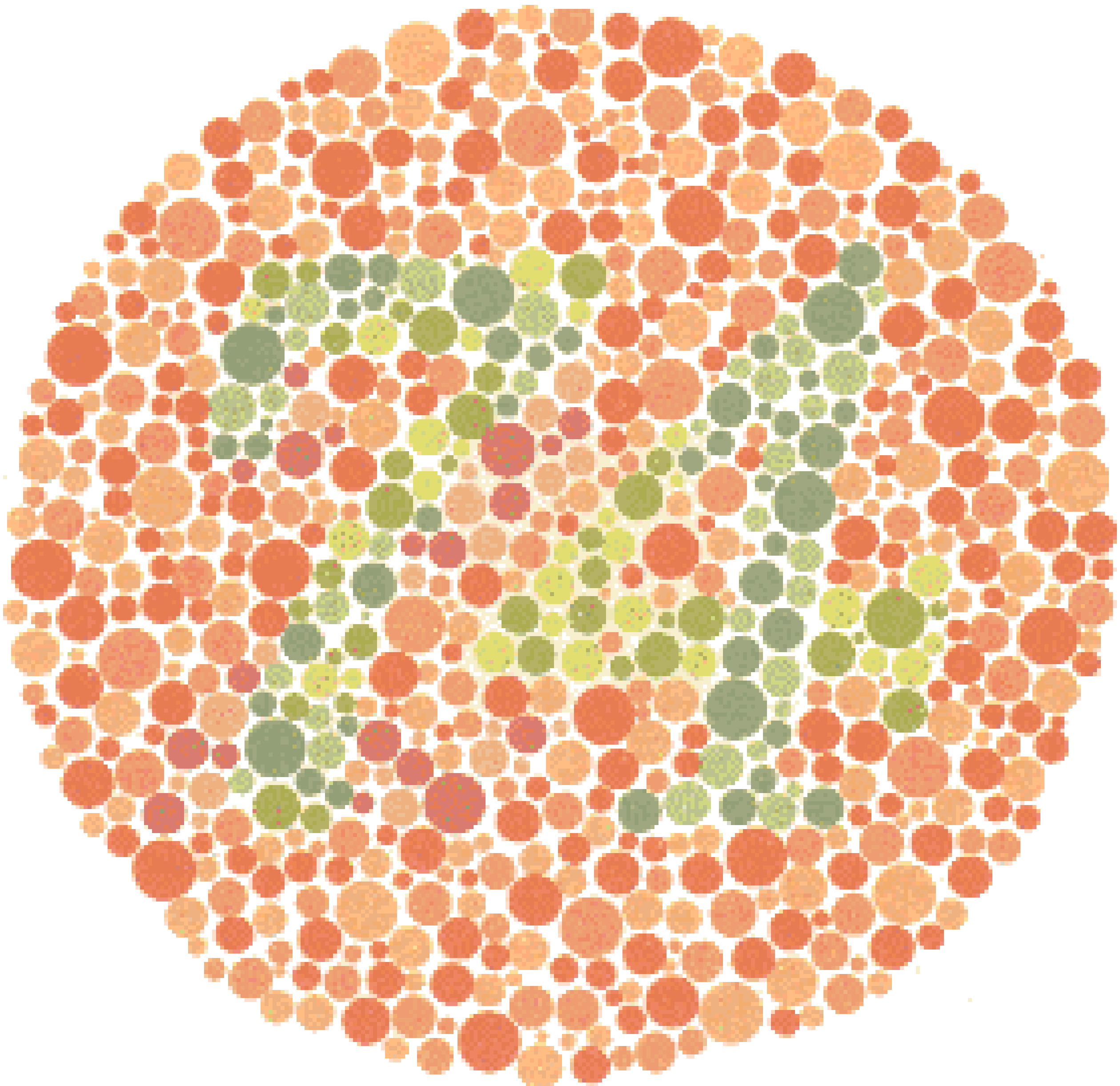


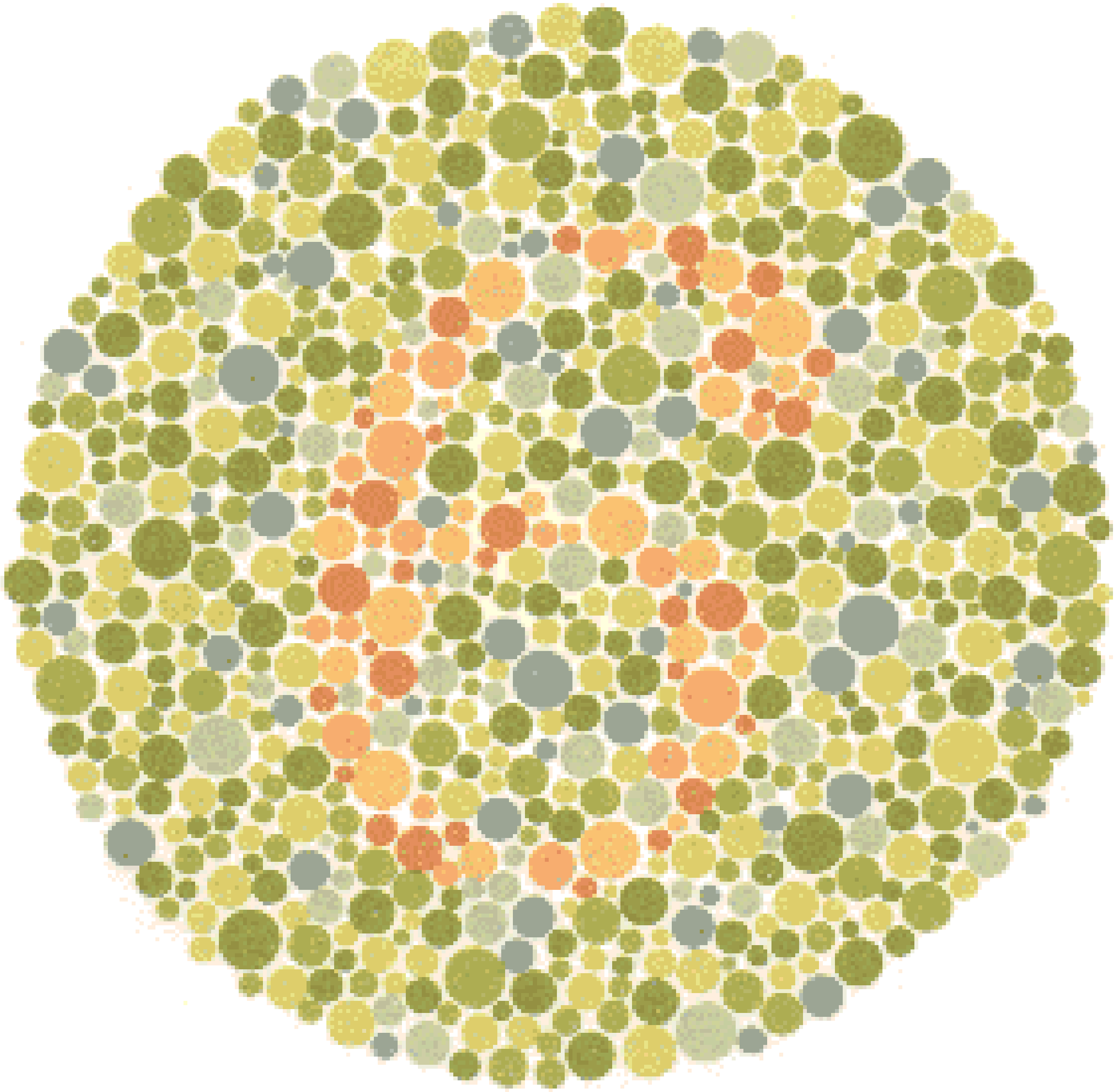


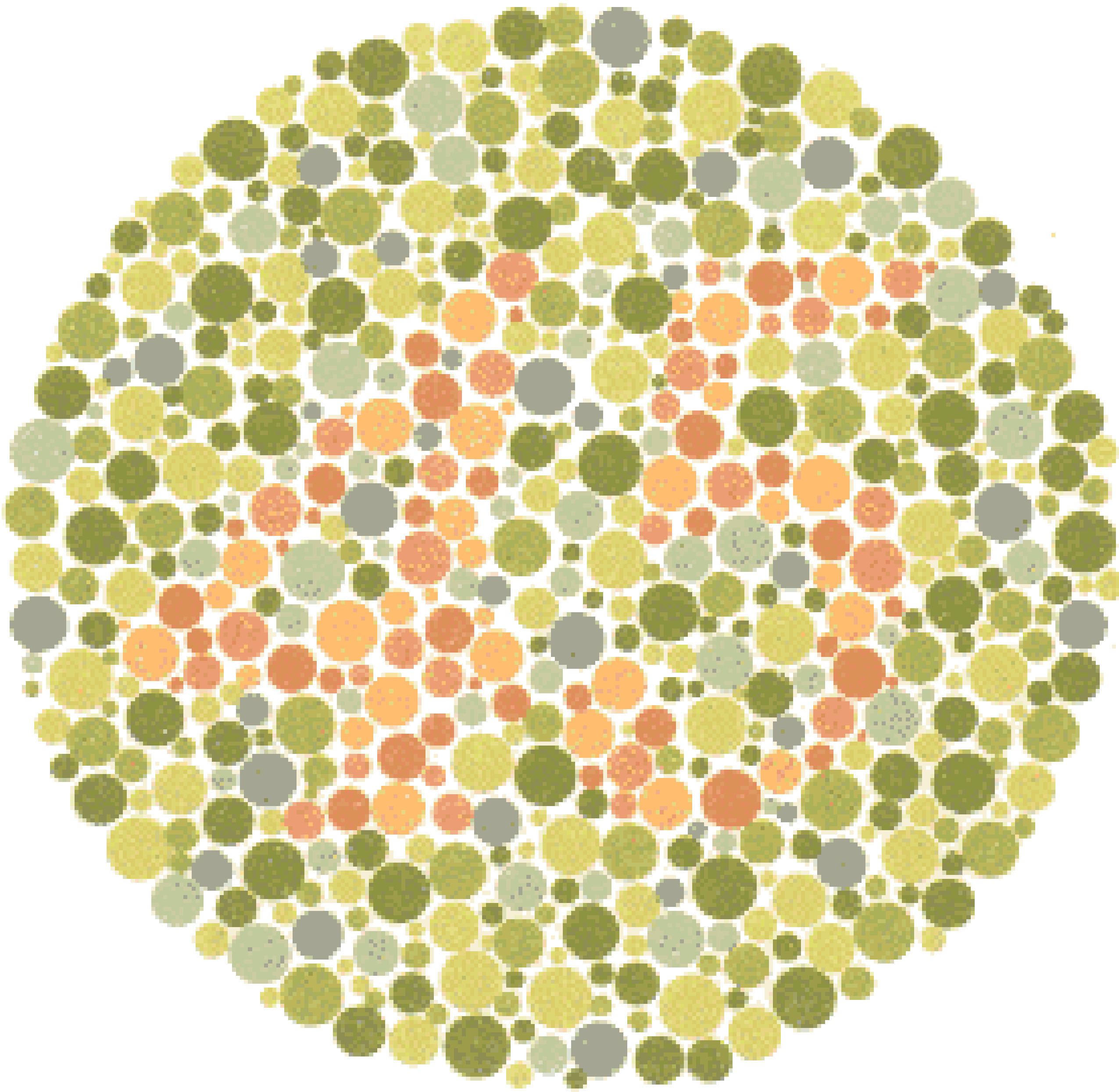


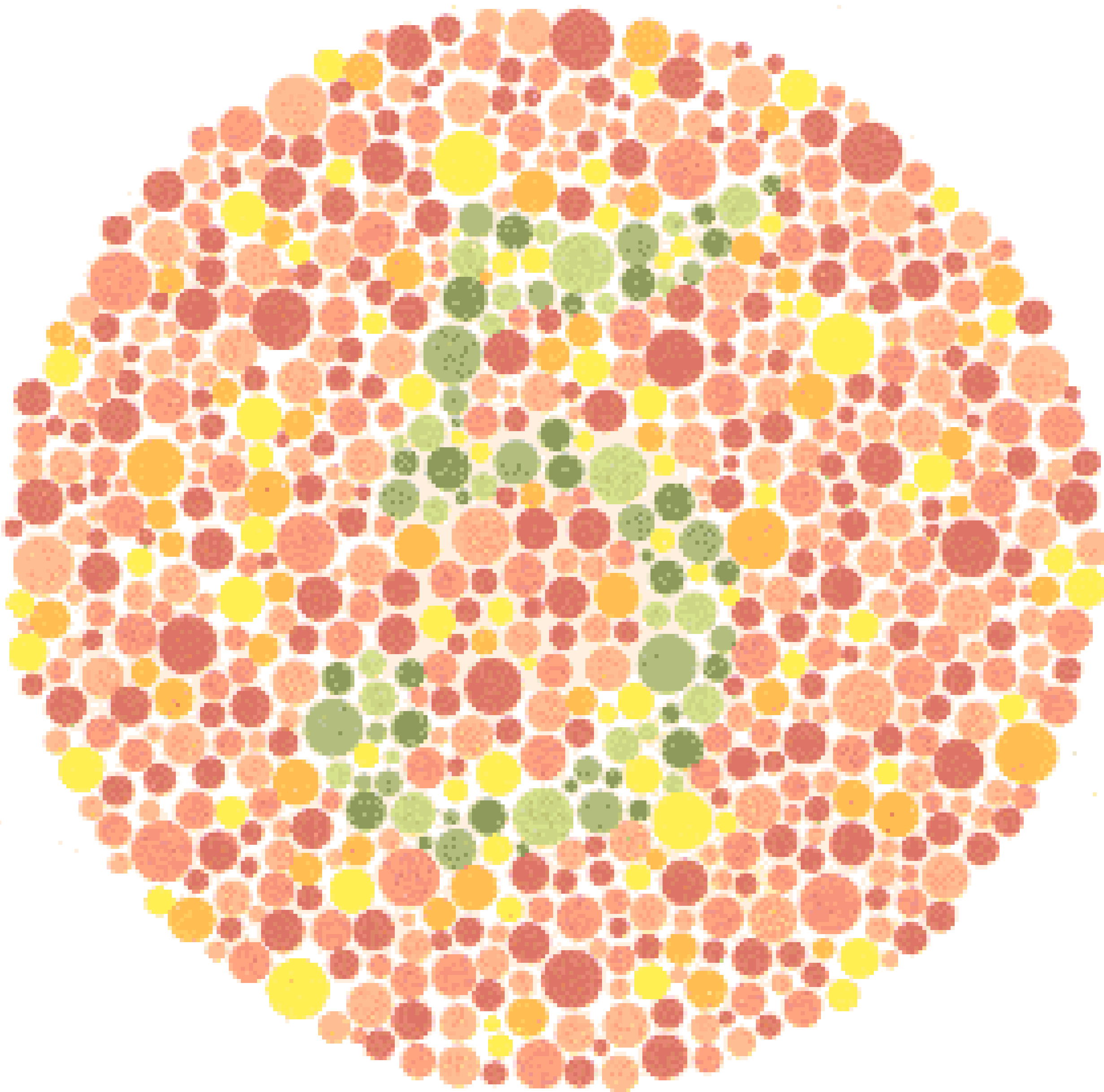


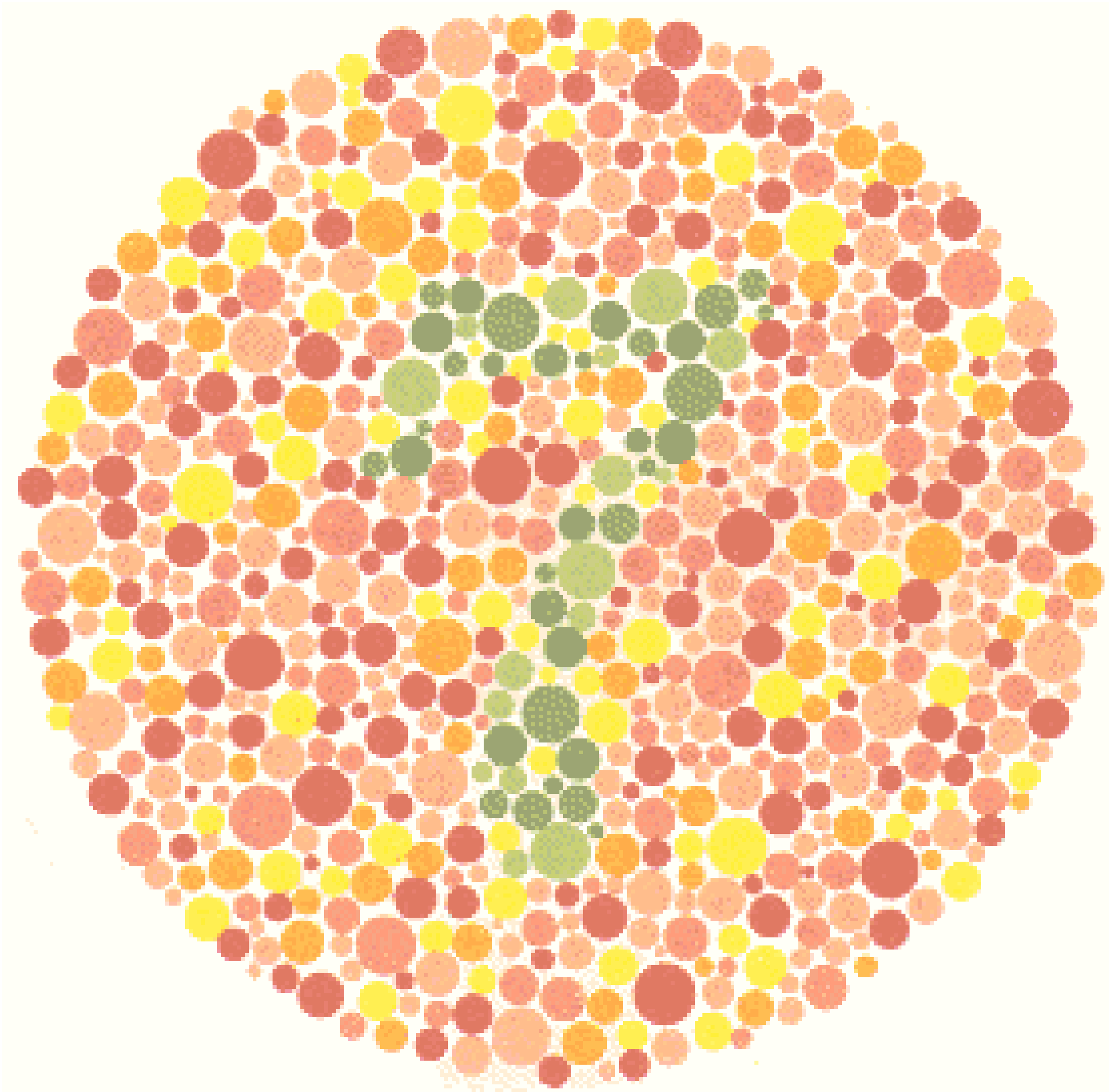


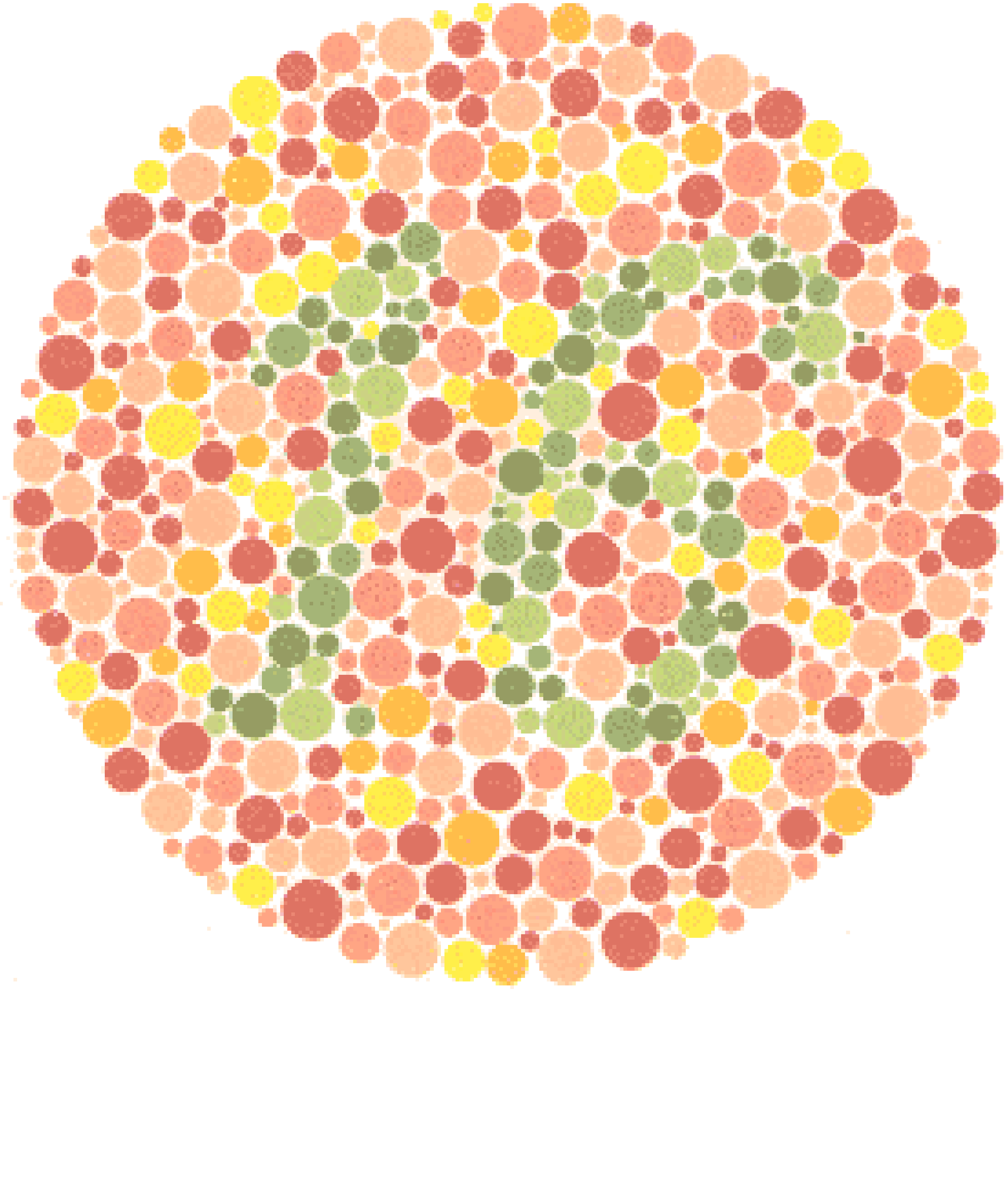


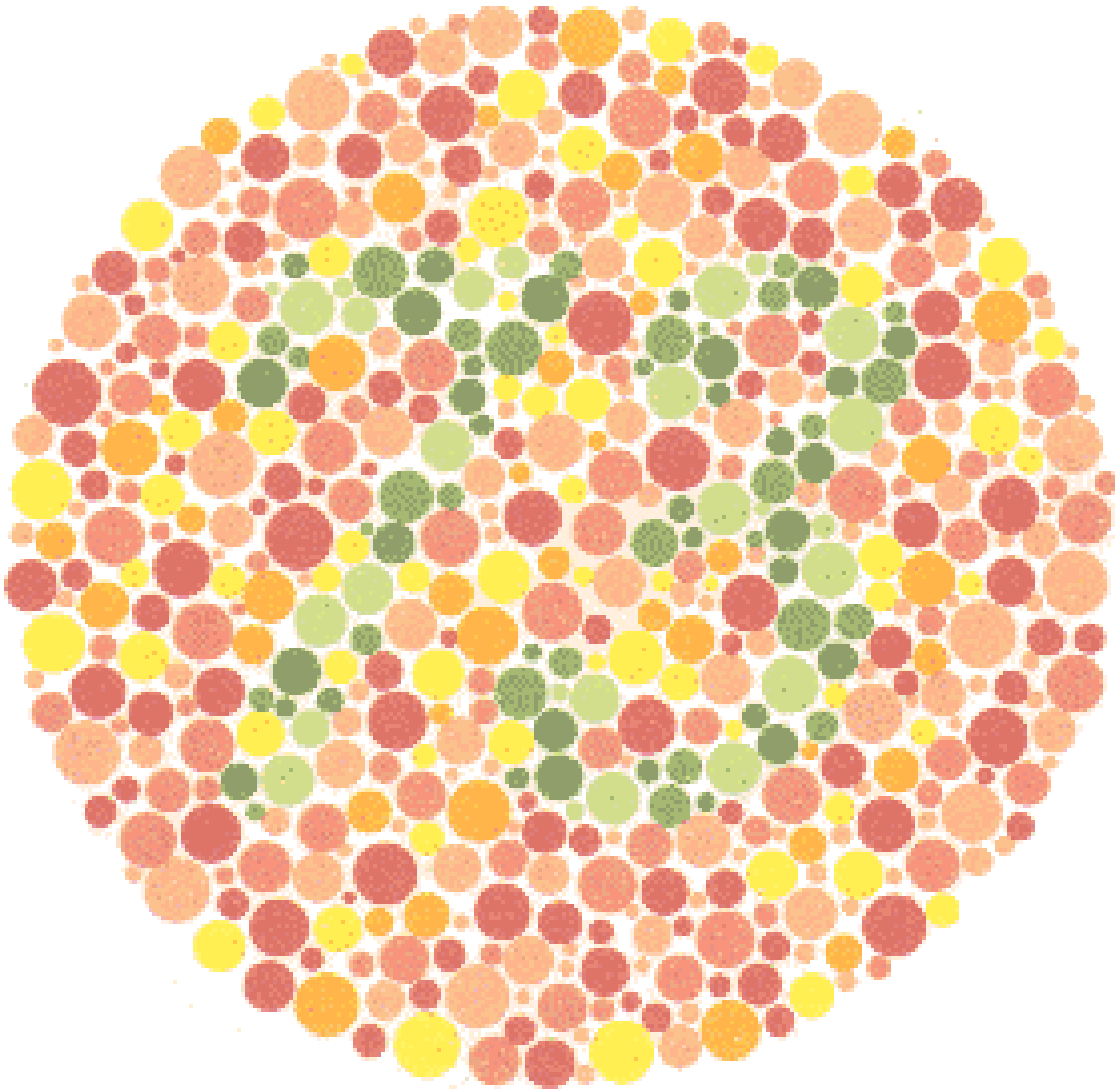


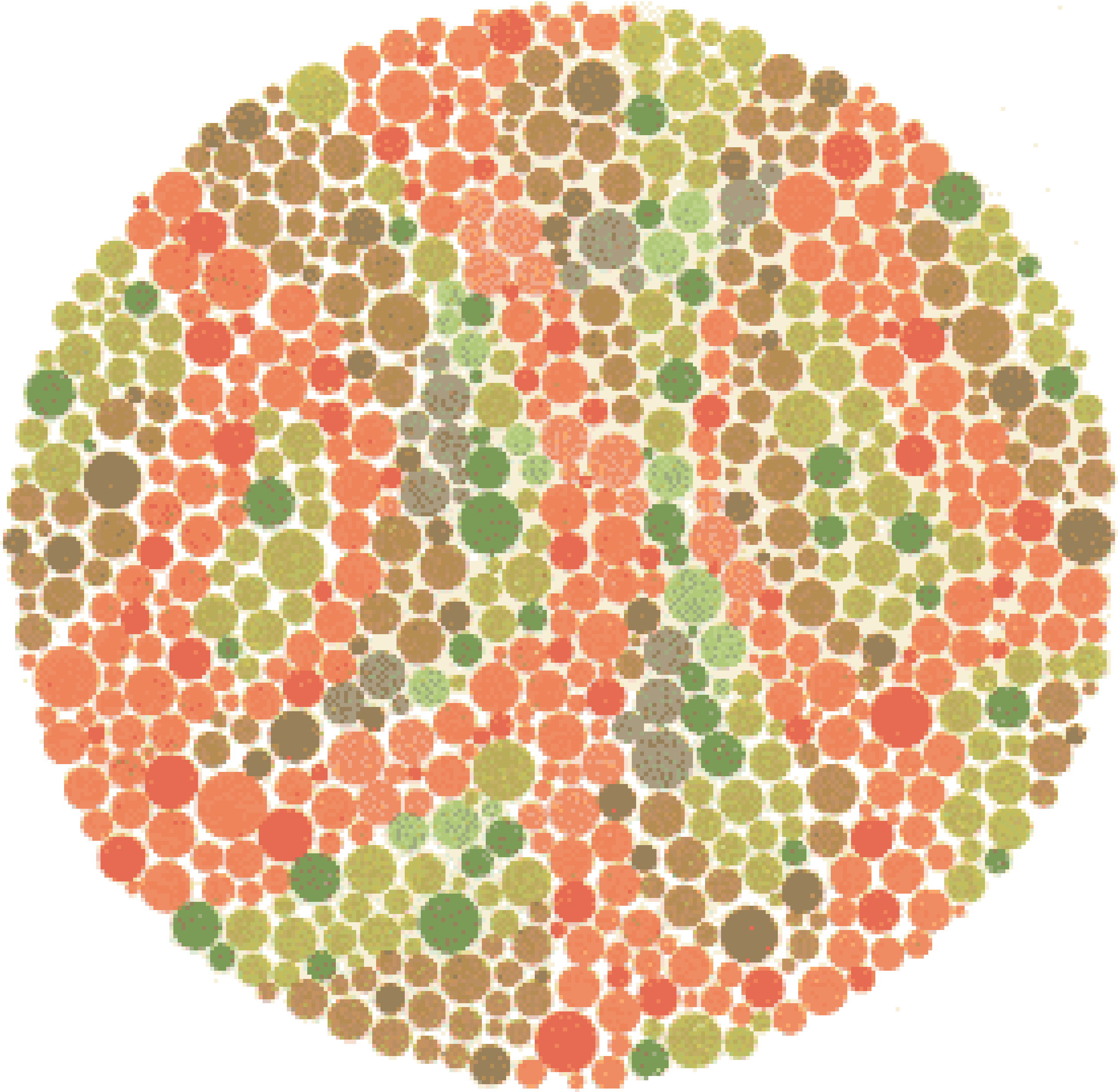


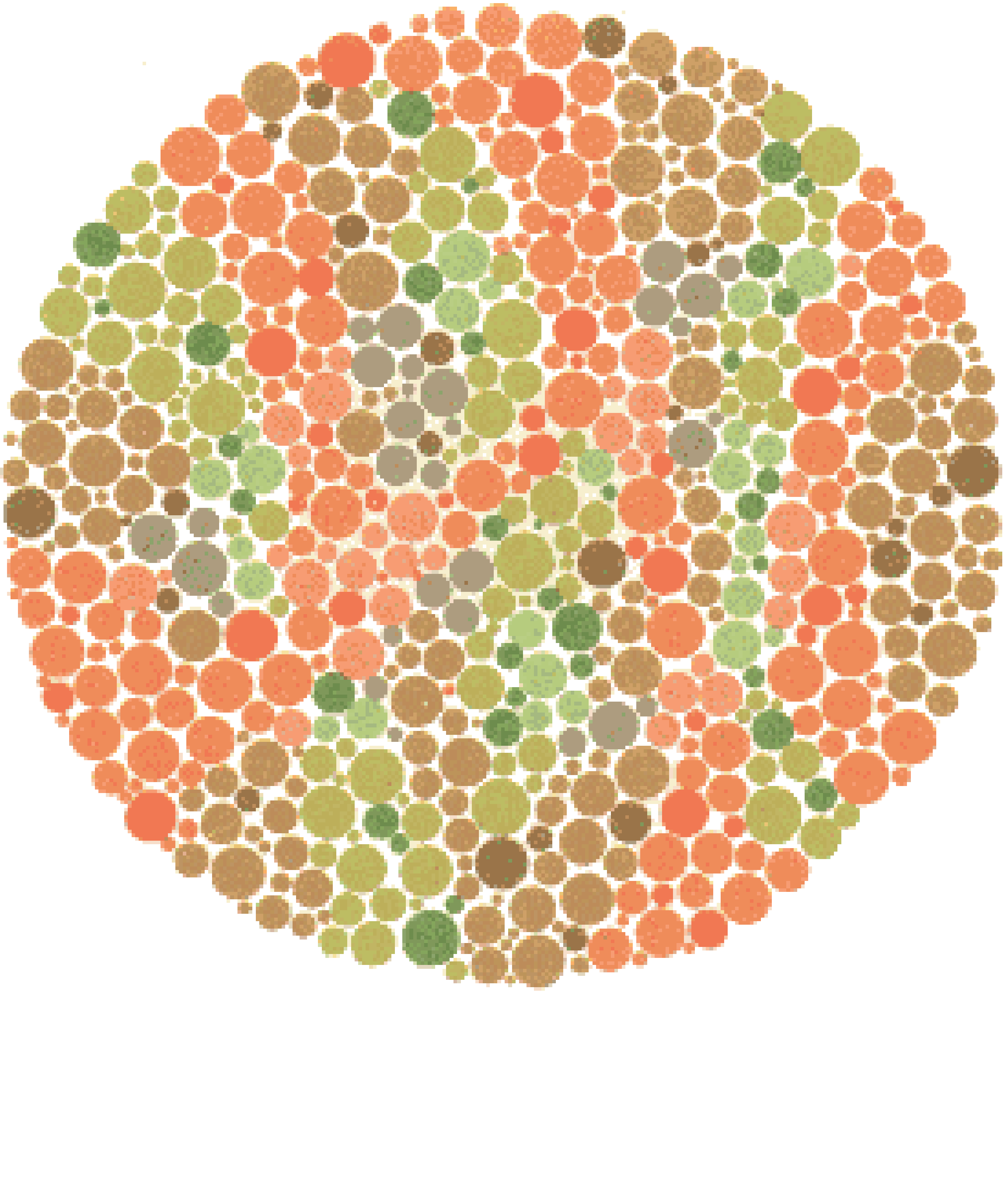


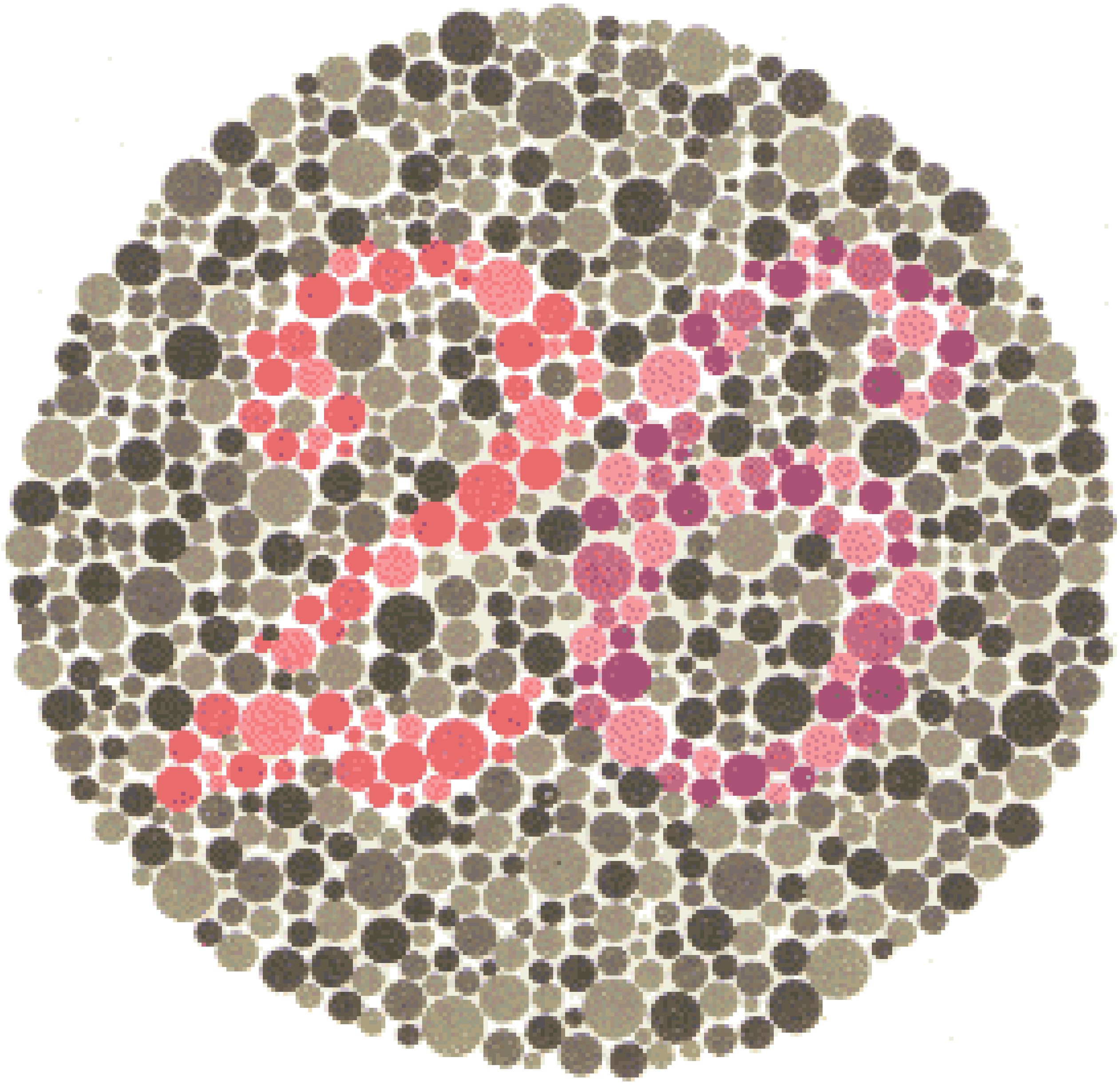


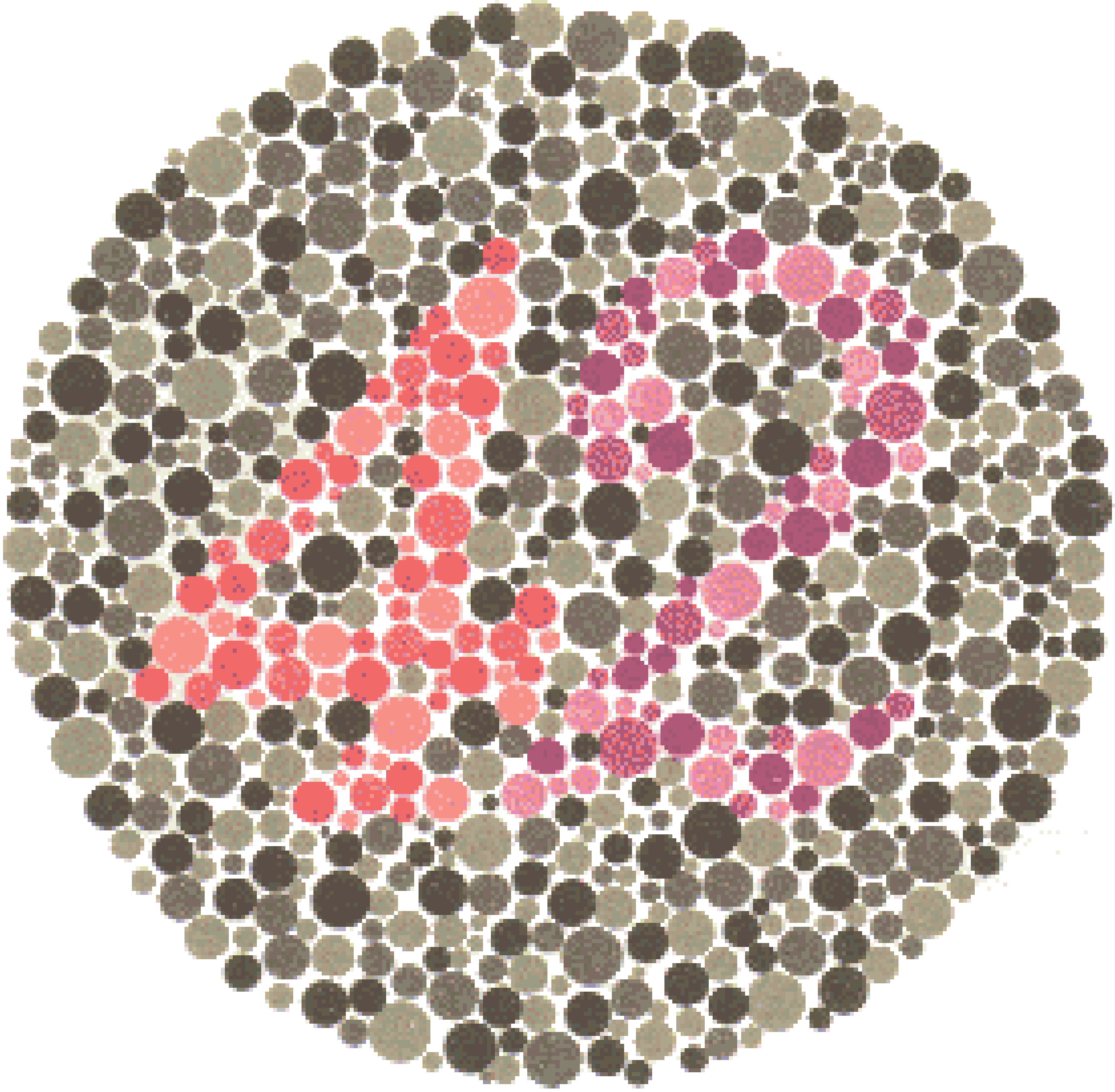


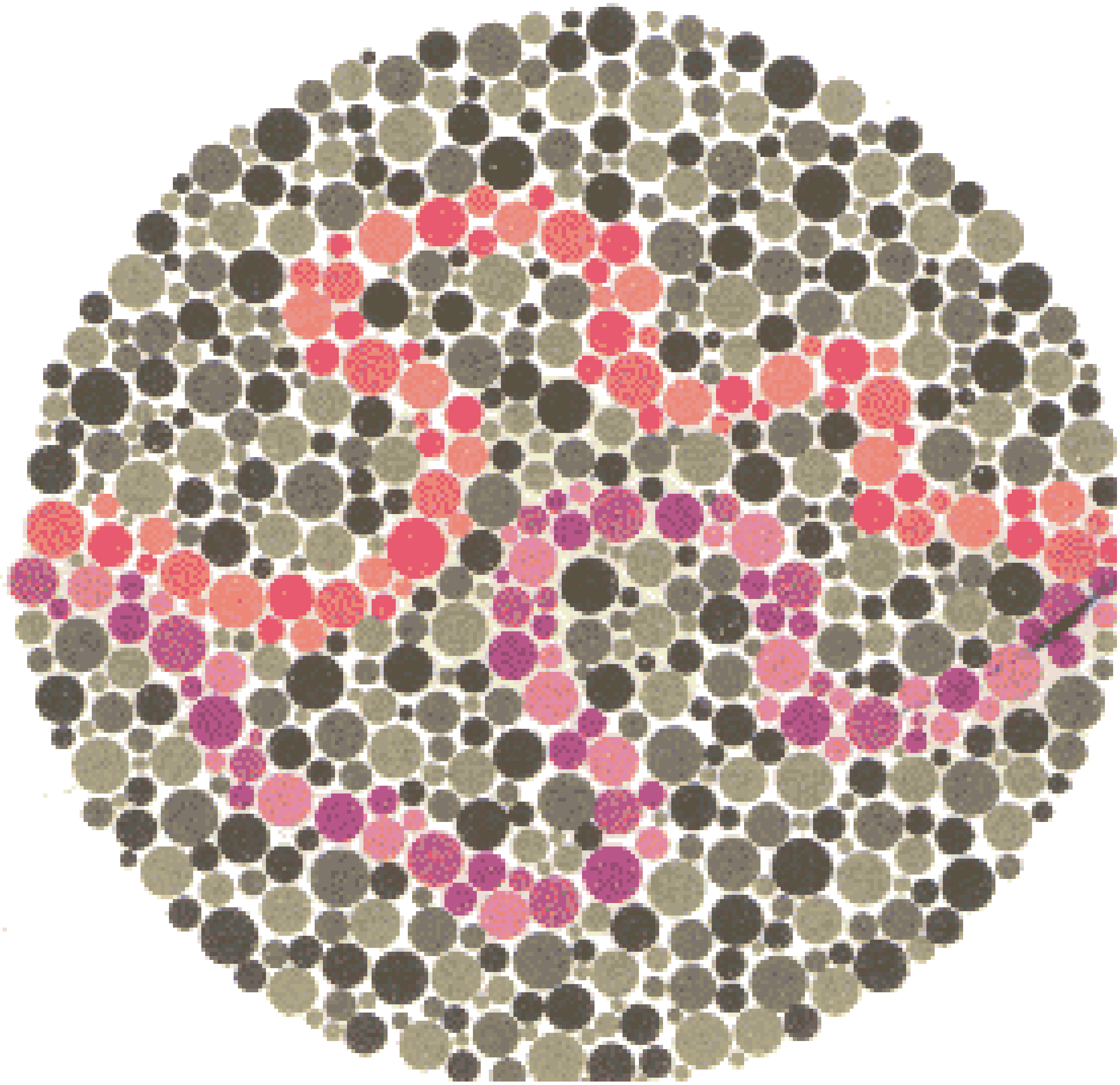


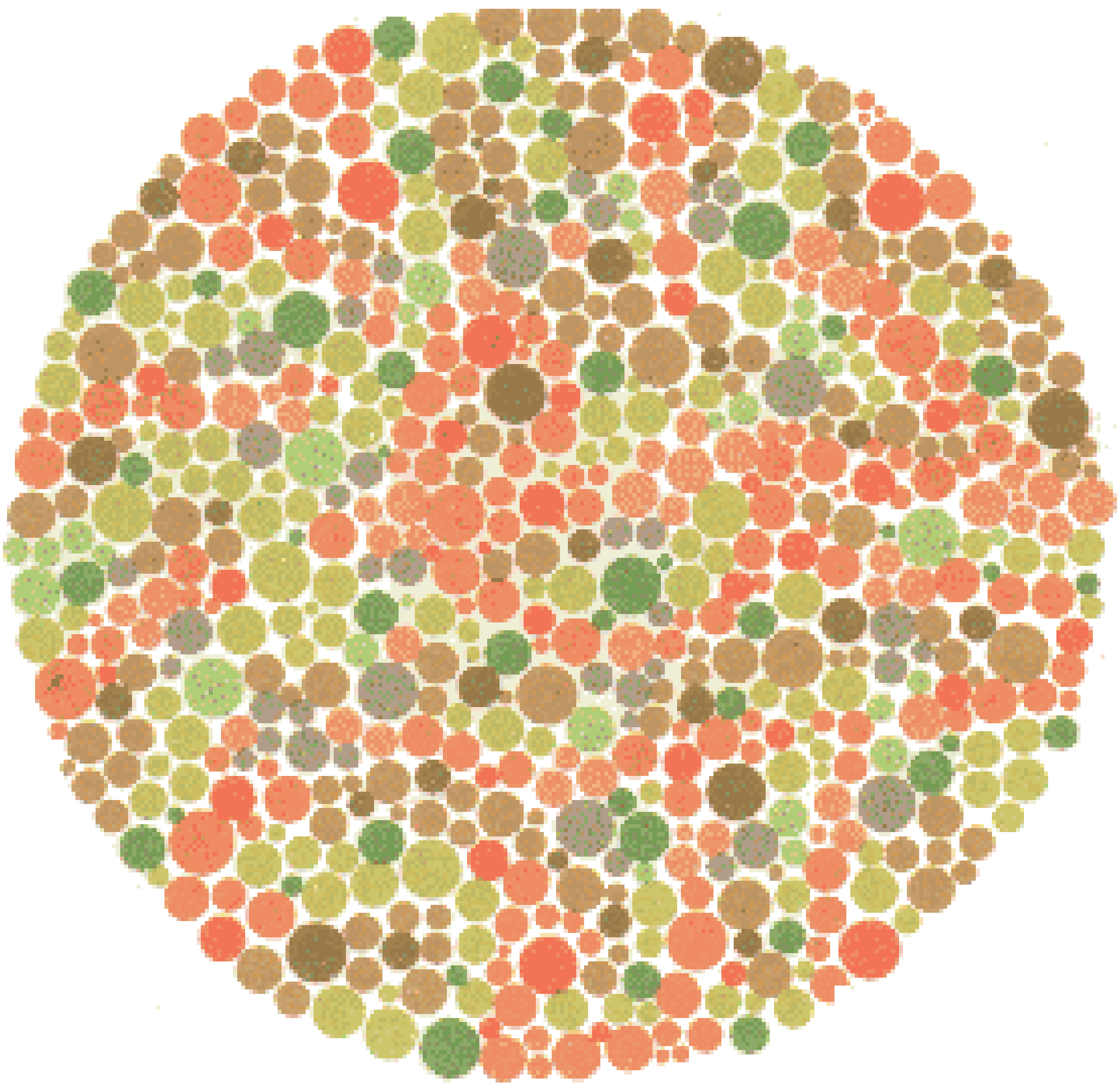


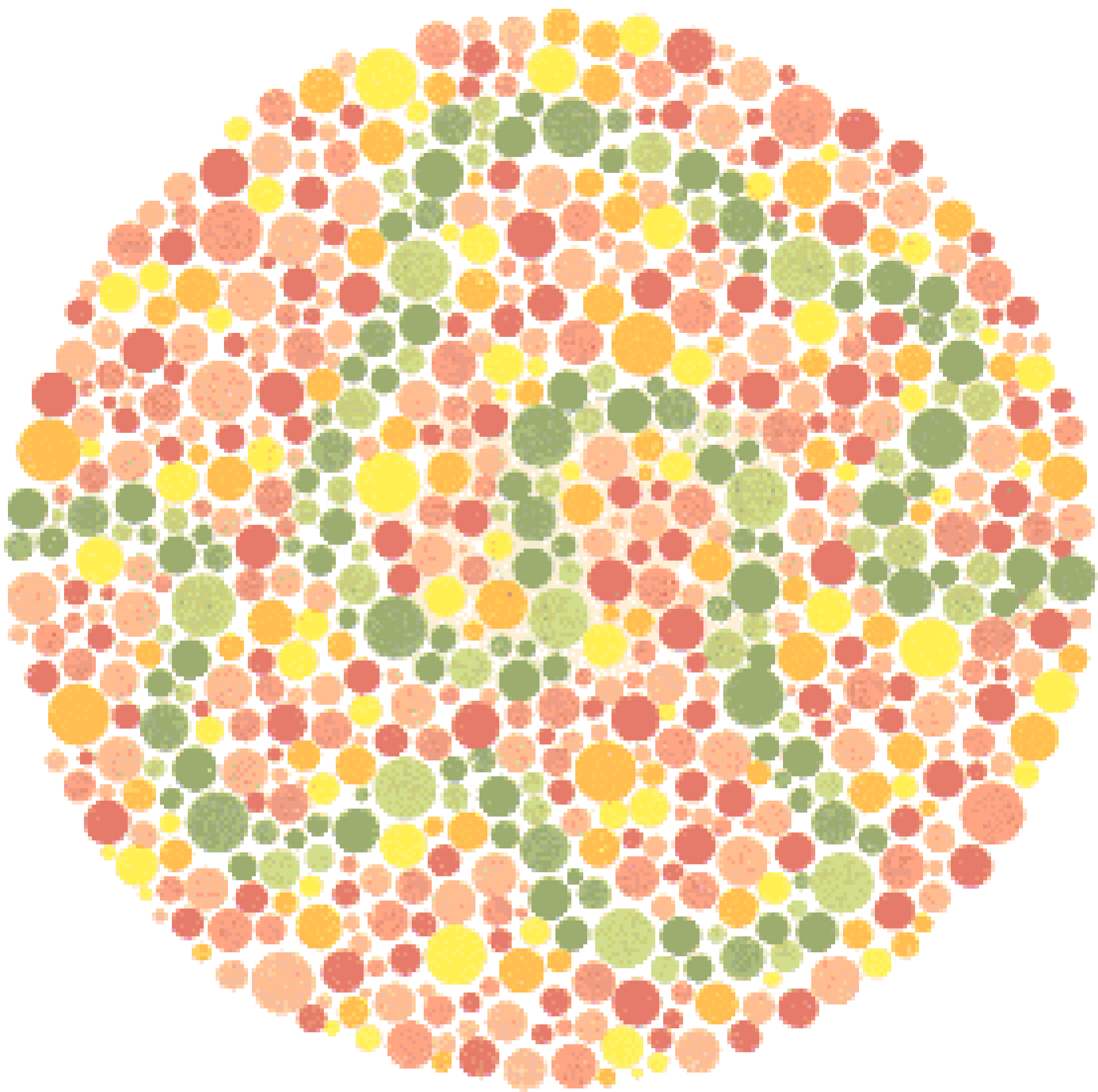


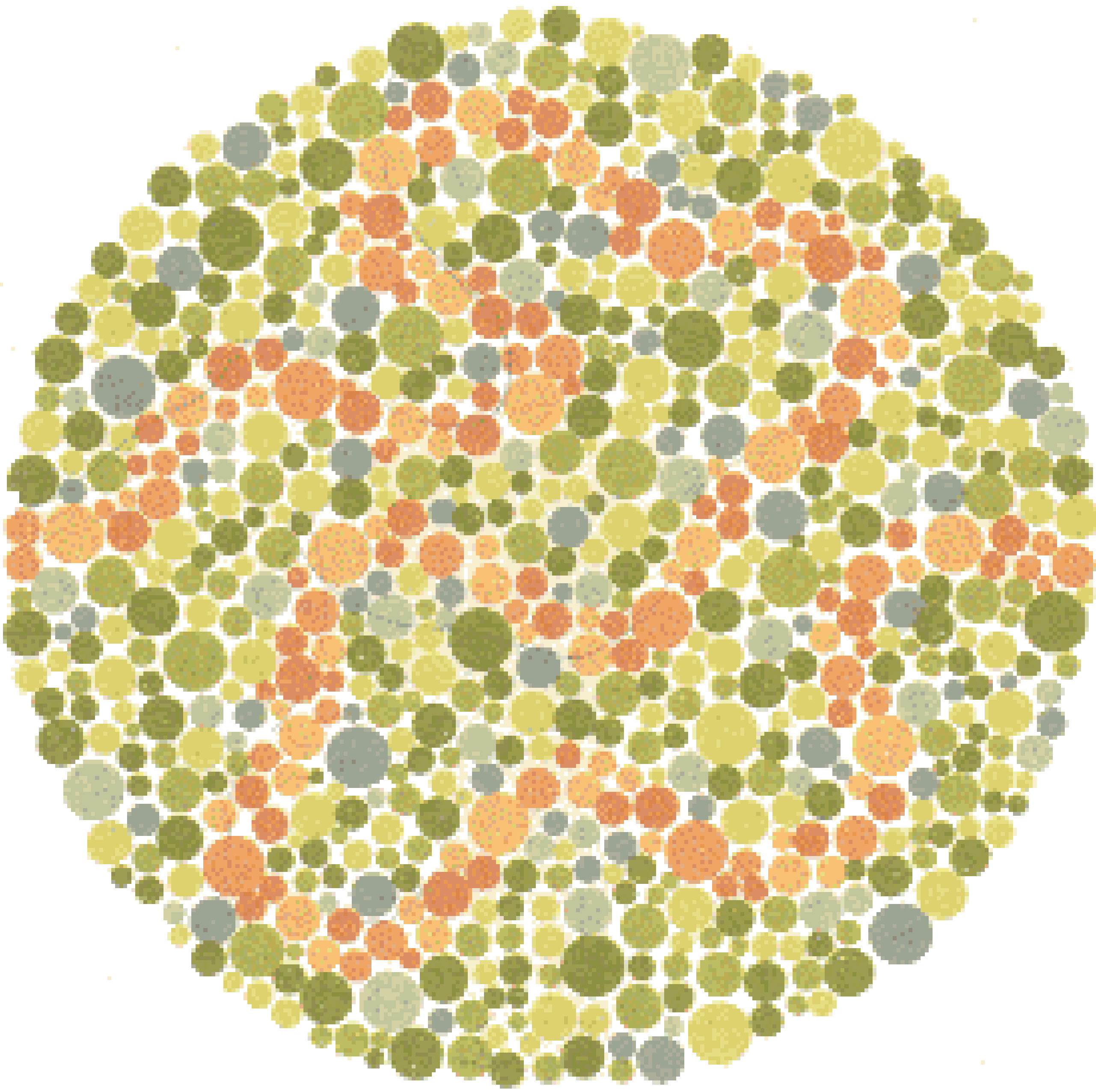


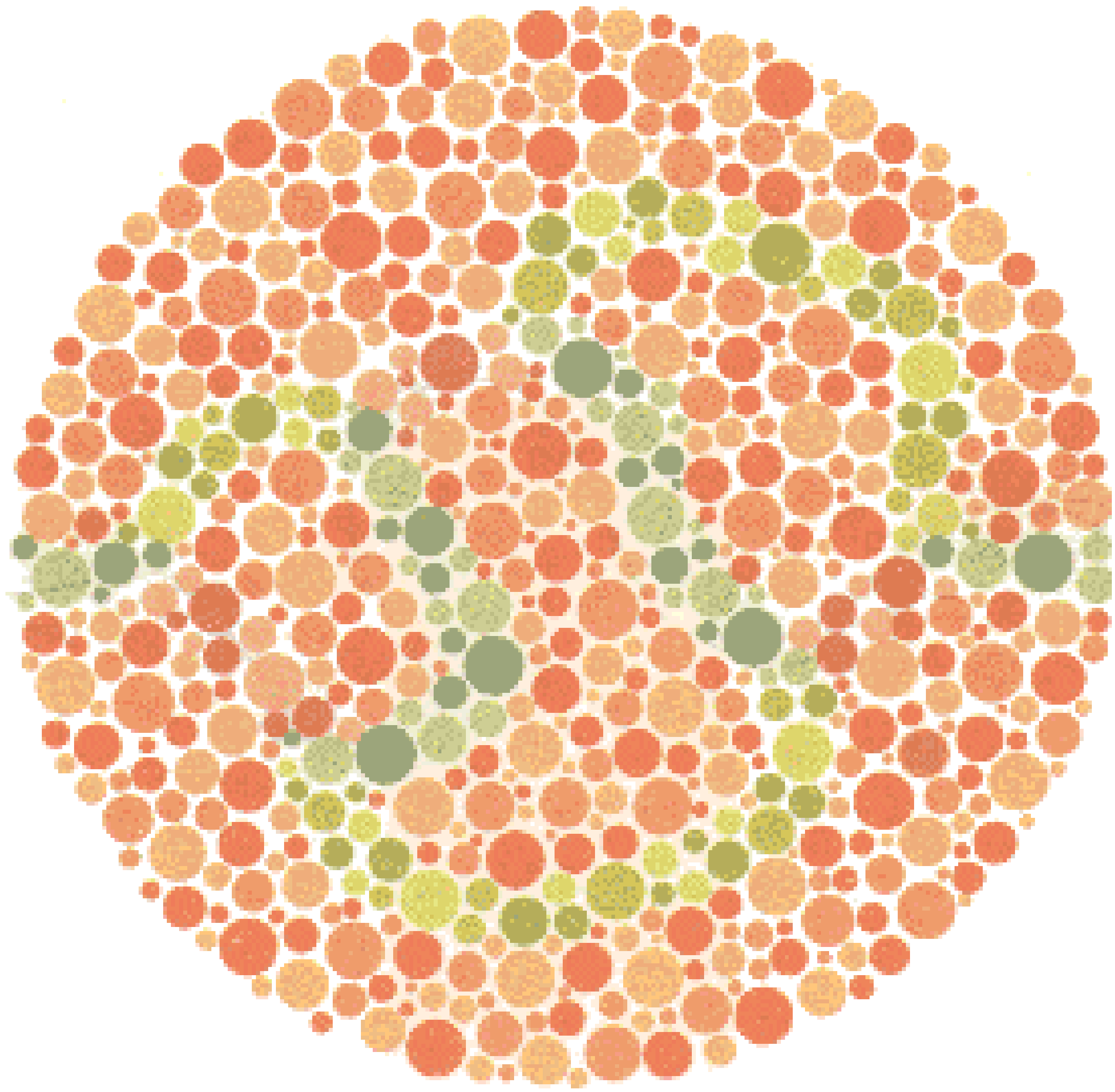


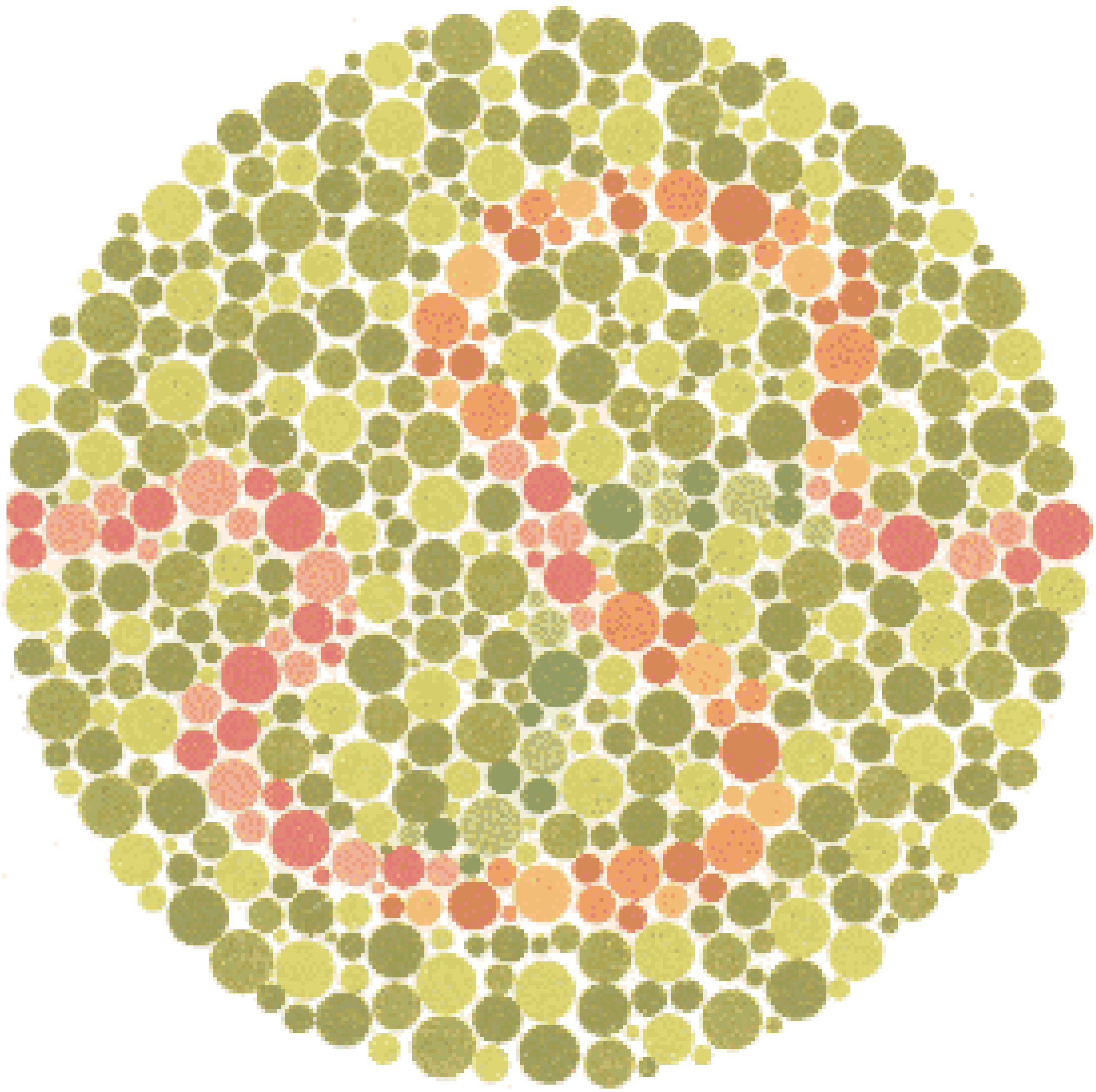


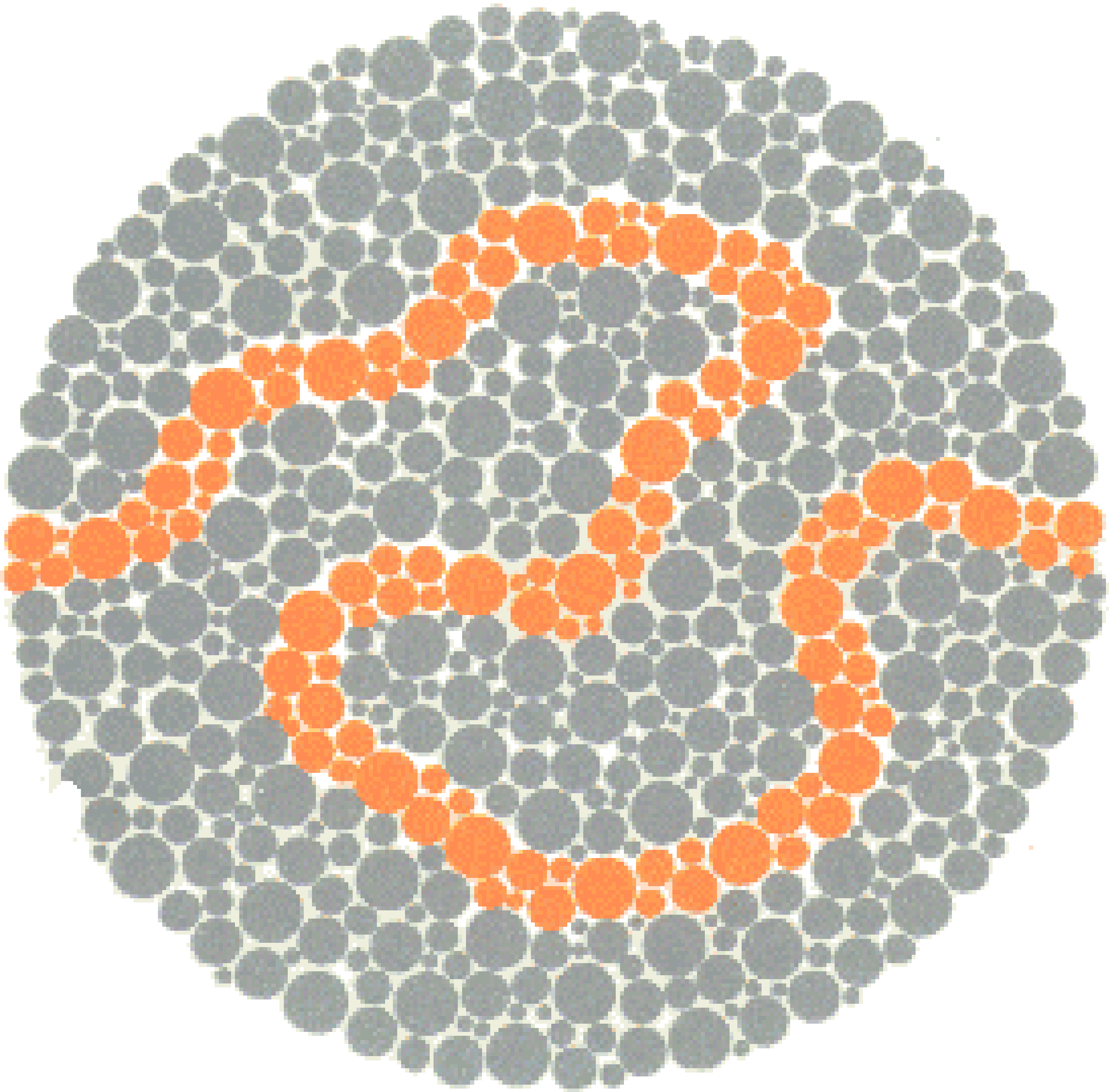












APPENDIX D: **SITUATION AWARENESS PROBES**

Situation Awareness Probes

L1

1) **What did the robot encounter?**
    a. Money Cache
    b. Weapon Cache
    c. Information Cache
    d. IED
    e. Intruder
    f. Nothing

2) **Did you observe any of the following?**
    a. Any Person
    b. Any Vehicle
    c. Nothing

3) **What is the robot doing?**
    a. Searching
    b. Documenting
    c. Dealing with Intruders

4) **What did you see that would affect your task or the robot's task?**
    a. Obstacle
    b. Intruder
    c. Nothing

L2

5) **Did you encounter a dangerous event?**
    a. Dangerous Person
    b. Dangerous Vehicle
    c. No dangerous event

6) **What is the robot's current priority?**
    a. Preserving Robot Safety
    b. Maintaining Information Flow

7) **What is your current priority?**
    a. Preserving Robot Safety

b. Maintaining Information Flow

L3

8) **What is the most likely outcome of the most current event you observed outside the building?**
    a. The robot might be damaged
    b. You might be in danger
    c. There's nothing for you to say
    d. Your communication system will lose energy as you use it
    e. You'll be delayed before making a decision

9) **If your priority was different, would your projected outcome change?**
    a. Yes
    b. No

10) **Given the most current event the robot encountered, what is the robot's most relevant projected outcome?**
    a. It will use energy
    b. It will be delayed
    c. It may be damaged
    d. It may suffer some signal interference

APPENDIX E: **TRANSACTIONAL QUERIES**

Transactional Query

In transactional communication conditions, the robot will ask the following question during each event:

1) What is your current priority?
    a. Information Flow
    b. Robot safety

APPENDIX F: **TRUST IN AUTOMATED SYSTEMS QUESTIONNAIRE**

Automation Survey

Automation refers to a system that reduces the need for human work. According to Lee and See (2004), "Automation is technology that actively selects data, transforms information, makes decisions, or controls processes." Below is a statement evaluating your feelings about automation. Please circle the number that best describes your feeling or impression.

1 = not at all; 7 = extremely

1. **Automation is deceptive**.
1 2 3 4 5 6 7

2. **Automation systems behave in an underhanded manner.**
1 2 3 4 5 6 7

3. **I am suspicious of the intent, action, or outputs of automation.**
1 2 3 4 5 6 7

4. **I am wary of automation.**
1 2 3 4 5 6 7

5. **The actions of automated systems will have harmful or injurious outcomes.**
1 2 3 4 5 6 7

6. **I am confident in automation.**
1 2 3 4 5 6 7

7. **Automated systems provide security.**
1 2 3 4 5 6 7

8. **Automated systems have integrity.**
1 2 3 4 5 6 7

9. **Automated systems are dependable.**
1 2 3 4 5 6 7

10. **Automated systems are reliable.**
1 2 3 4 5 6 7

11. **I can trust automated systems.**
1 2 3 4 5 6 7

12. **I am familiar with automation.**
1 2 3 4 5 6 7

Jian, J. Y., Bisantz, A. M., & Drury, C. G. (2000). Foundations for an empirically determined scale of trust in automated systems. *International Journal of Cognitive Ergonomics*, *4*(1), 53-71.

Scoring: 1-5 Reverse Coded, 6-12 traditional coding.

APPENDIX G: **IMPLICIT ATTITUDE TEST**

Implicit Attitude Test

IATs use response latencies to measure implicit associations, with shorter response latencies representing stronger associations and thus a stronger preference. An IAT for automation will be undertaken to measure implicit trust in automation. The evaluative category (i.e., good/bad) words were adopted from Project Implicit's race IAT (words used: joy, love, peace, wonderful, pleasure, glorious, laughter, happy; agony, terrible, horrible, nasty, evil, awful, failure, hurt). During the IAT, participants were asked to categorize good words (e.g., marvelous, superb), bad words (e.g., tragic, horrible), words representing humans (human and person), and those representing automation (automation and machine) into their superordinate categories (i.e., good/bad or automation/human).

The Superordinate Categories (exemplars) are:
Humans (Human, Person)
Automation (Automation, Machine)
Good (Joy, Love, Peace, Wonderful, Pleasure, Glorious, Laughter, Happy)
Bad (Agony, terrible, Horrible, Nasty, Evil, Awful, Failure, Hurt)

There are 7 stages

Stage 1:
Automation Human

(the words Automation, Machine, Human, and Person appear on screen. Users associate the Automation words with Automation and the Human words with Human)

Stage 2:
Good Bad

(the words Joy, Love, Peace, Wonderful, Pleasure, Glorious, Laughter, Happy, Agony, terrible, Horrible, Nasty, Evil, Awful, Failure, and Hurt appear on screen. Users associate the Good words with Good and the Bad words with Bad)

Stage 3:
Automation Human
Good Bad

(the words Joy, Love, Peace, Wonderful, Pleasure, Glorious, Laughter, Happy, Agony, terrible, Horrible, Nasty, Evil, Awful, Failure, Hurt, Automation, Machine, Human, and Person appear on screen. Users associate the Good words with Good, the Bad words with Bad, the Automation words with Automation, and the Human words with Human)

Stage 4:
Automation Human
Good Bad

(the words Joy, Love, Peace, Wonderful, Pleasure, Glorious, Laughter, Happy, Agony, terrible, Horrible, Nasty, Evil, Awful, Failure, Hurt, Automation, Machine, Human, and Person appear on screen. Users associate the Good words with Good, the Bad words with Bad, the Automation words with Automation, and the Human words with Human)

Stage 5:
Bad Good

(the words Joy, Love, Peace, Wonderful, Pleasure, Glorious, Laughter, Happy, Agony, terrible, Horrible, Nasty, Evil, Awful, Failure, and Hurt appear on screen. Users associate the Good words with Good and the Bad words with Bad)

Stage 6:
Automation Human
Bad Good

(the words Joy, Love, Peace, Wonderful, Pleasure, Glorious, Laughter, Happy, Agony, terrible, Horrible, Nasty, Evil, Awful, Failure, Hurt, Automation, Machine, Human, and Person appear on screen. Users associate the Good words with Good, the Bad words with Bad, the Automation words with Automation, and the Human words with Human)

Stage 7:
Automation Human
Bad Good

(the words Joy, Love, Peace, Wonderful, Pleasure, Glorious, Laughter, Happy, Agony, terrible, Horrible, Nasty, Evil, Awful, Failure, Hurt, Automation, Machine, Human, and Person appear on screen. Users associate the Good words with Good, the Bad words with Bad, the Automation words with Automation, and the Human words with Human)

In each stage, participants are confronted with 20 exemplars (except Stages 4 & 7 which each have 40), repetitions are allowed. Typically, words associated with the category on the left is indicated with "e," while the words associated with the category on the right is indicated with "i." Mis-attributing can be corrected, but will be signified with a red x on screen.

Scoring:

$$D = \frac{\left(\frac{M_{\text{Block 6}} - M_{\text{Block 3}}}{SD_{Pooled\ Blocks\ \text{3\&6}}}\right) + \left(\frac{M_{\text{Block 7}} - M_{\text{Block 4}}}{SD_{Pooled\ Blocks\ \text{4\&7}}}\right)}{2}$$

Scoring from:
Nosek, B. A., Greenwald, A. G., & Banaji, M. R. (2005). Understanding and using the Implicit Association Test: II. Method variables and construct validity. *Personality and Social Psychology Bulletin*, *31*(2), 166-180.

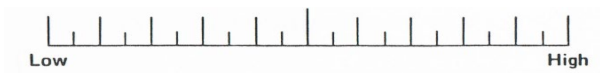
Contents from:
Merritt, S. M., Heimbaugh, H., LaChapell, J., & Lee, D. (2012). I Trust It, but I Don't Know Why Effects of Implicit Attitudes Toward Automation on Trust in an Automated System. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 0018720812465081.

APPENDIX H: **NASA-TLX**

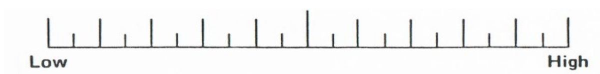
NASA-TLX Questionnaire

Please rate your <u>overall</u> impression of demands imposed on you during the exercise.

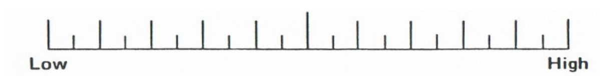
1. Mental Demand: How much mental and perceptual activity was required (e.g., thinking, looking, searching, etc.)? Was the task easy or demanding, simple or complex, exacting or forgiving?



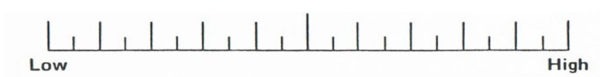
2. Physical Demand: How much physical activity was required (e.g., pushing, pulling, turning, controlling, activating, etc.)? Was the task easy or demanding, slow or brisk, slack or strenuous, restful or laborious?



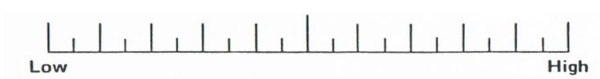
3. Temporal Demand: How much time pressure did you feel due to the rate or pace at which the task or task elements occurred? Was the pace slow and leisurely or rapid and frantic?



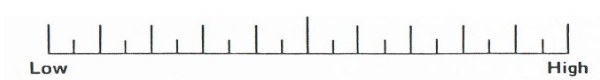
4. Level of Effort: How hard did you have to work (mentally and physically) to accomplish your level of performance?



5. Level of Frustration: How insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent did you feel during the task?



6. Performance: How successful do you think you were in accomplishing the goals of the task set by the experimenter (or yourself)? How satisfied were you with your performance in accomplishing these goals?



Pairwise Comparison of Factors

Select the member of each pair that provided the most significant source of workload variation in these tasks.

Physical Demand vs. Mental Demand

Temporal Demand vs. Mental Demand

Performance vs. Mental Demand

Frustration vs. Mental Demand

Effort vs. Mental Demand

Temporal Demand vs. Physical Demand

Performance vs. Physical Demand

Frustration vs. Physical Demand

Effort vs. Physical Demand

Temporal Demand vs. Performance

Temporal Demand vs. Frustration

Temporal Demand vs. Effort

Performance vs. Frustration

Performance vs. Effort

Effort vs. Frustration

Hart, S. G., & Staveland, L. E. (1988). Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. *Advances in psychology*, *52*, 139-183.

APPENDIX I**: GODSPEED QUESTIONNAIRE SERIES**

Godspeed Questionnaire Series

GODSPEED I: ANTHROPOMORPHISM

Please rate your impression of the robot on these scales:

Fake	1	2	3	4	5	Natural
Machinelike	1	2	3	4	5	Humanlike
Unconscious	1	2	3	4	5	Conscious
Artificial	1	2	3	4	5	Lifelike
Moving rigidly	1	2	3	4	5	Moving elegantly

GODSPEED II: ANIMACY

Please rate your impression of the robot on these scales:

Dead	1	2	3	4	5	Alive
Stagnant	1	2	3	4	5	Lively
Mechanical	1	2	3	4	5	Organic
Artificial	1	2	3	4	5	Lifelike
Inert	1	2	3	4	5	Interactive
Apathetic	1	2	3	4	5	Responsive

GODSPEED III: LIKEABILITY

Please rate your impression of the robot on these scales:

Dislike	1	2	3	4	5	Like
Unfriendly	1	2	3	4	5	Friendly
Unkind	1	2	3	4	5	Kind
Unpleasant	1	2	3	4	5	Pleasant
Awful	1	2	3	4	5	Nice

GODSPEED IV: PERCEIVED INTELLIGENCE

Please rate your impression of the robot on these scales:

Incompetent	1	2	3	4	5	Competent
Ignorant	1	2	3	4	5	Knowledgeable
Irresponsible	1	2	3	4	5	Responsible
Unintelligent	1	2	3	4	5	Intelligent
Foolish	1	2	3	4	5	Sensible

GODSPEED V: PERCEIVED SAFETY

Please rate your emotional state on these scales:

Anxious	1	2	3	4	5	Relaxed
Agitated	1	2	3	4	5	Calm
Quiescent	1	2	3	4	5	Surprised

To score, calculate the mean for each scale

According to the author, when one questionnaire is used alone it is best to mask the intent by adding several dummy questions. If multiple questionnaires are used the items should be mixed so as to mask intent. A masked version for lab use is shown on the following page, scoring following.

Citation:

Bartneck, C., Kulić, D., Croft, E., & Zoghbi, S. (2009). Measurement instruments for the anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety of robots. *International Journal of Social Robotics*, *1*(1), 71-81.

APPENDIX J: **PERFORMANCE DESCRIPTIVE STATISTICS TABLES**

Table J - 1. Descriptive statistics for correct identifications by experimental conditions

Condition	***N***	***M***	***SD***	***SE***
TT+TC	40	26.7000	1.26491	0.20000
AT+TC	40	26.2750	2.19542	0.34713
TT+UC	40	26.5750	2.27458	0.35964
AT+UC	40	27.3000	1.11401	0.17614

Table J - 2. Descriptive statistics for incorrect identifications by experimental conditions

Condition	***N***	***M***	***SD***	***SE***
TT+TC	40	0.2500	0.54302	0.08586
AT+TC	40	0.4750	0.93336	0.14758
TT+UC	40	0.3250	0.91672	0.14495
AT+UC	40	0.1250	0.40430	0.06393

Table J - 3. Descriptive statistics for misses by experimental conditions

Condition	***N***	***M***	***SD***	***SE***
TT+TC	40	1.0500	1.03651	0.16389
AT+TC	40	1.2500	1.51488	0.23952
TT+UC	40	1.1000	1.69161	0.26747
AT+UC	40	0.5750	0.98417	0.15561

Table J - 4. Descriptive statistics for median reaction time (in milliseconds) by experimental conditions

Condition	*N*	*M*	*SD*	*SE*
TT+TC	40	1976.0625	432.60769	68.40128
AT+TC	40	1855.3875	383.44910	60.62863
TT+UC	40	1877.7500	392.53830	62.06576
AT+UC	40	1875.3500	391.70587	61.93414

APPENDIX K: **SITUATION AWARENESS DESCRIPTIVE STATISTICS TABLES**

Table K - 1. Descriptive statistics for overall situation awareness scores by experimental conditions

Condition	***N***	***M***	***SD***	***SE***
TT+TC	40	0.6685	0.08909	0.01409
AT+TC	40	0.6700	0.09974	0.01714
TT+UC	40	0.6740	0.10843	0.01577
AT+UC	40	0.6643	0.10230	0.01618

Table K - 2. Descriptive statistics for level 1 situation awareness scores by experimental conditions

Condition	***N***	***M***	***SD***	***SE***
TT+TC	40	0.7750	0.12036	0.01903
AT+TC	40	0.8025	0.12034	0.01903
TT+UC	40	0.7813	0.12073	0.01909
AT+UC	40	0.7838	0.12577	0.01989

Table K - 3. Descriptive statistics for level 2 situation awareness scores by experimental conditions

Condition	***N***	***M***	***SD***	***SE***
TT+TC	40	0.7683	0.14401	0.02277
AT+TC	40	0.7233	0.15063	0.02382
TT+UC	40	0.7633	0.16256	0.02570
AT+UC	40	0.7183	0.19942	0.03153

Table K - 4. Descriptive statistics for level 3 situation awareness scores by experimental conditions

Condition	***N***	***M***	***SD***	***SE***
TT+TC	40	0.4267	0.16386	0.02591
AT+TC	40	0.4400	0.14065	0.02224
TT+UC	40	0.4417	0.14456	0.02286
AT+UC	40	0.4227	0.14897	0.02355

APPENDIX L: **OVERALL WORKLOAD DESCRIPTIVE STATISTICS TABLES**

Table L - 1. Descriptive statistics for overall workload scores by experimental conditions

Condition	***N***	***M***	***SD***	***SE***
TT+TC	40	47.3333	15.71447	2.48468
AT+TC	40	42.3958	18.86957	2.98354
TT+UC	40	44.1875	16.53957	2.61514
AT+UC	40	43.6667	17.47893	2.76366

APPENDIX M:**TRUST DESCRIPTIVE STATISTICS TABLES**

Table M - 1. Descriptive statistics for IAT trust scores by association pair seen first

Association Order	***N***	***M***	***SD***	***SE***
Automation + Good	20	-0.3442	0.34168	0.07640
Automation + Bad	20	0.5475	0.19164	0.04285

Table M - 2. Descriptive statistics for IAT trust z-scores by association pair seen first

Association Order	***N***	***M***	***SD***	***SE***
Automation + Good	20	-0.3442	0.34168	0.07640
Automation + Bad	20	0.5475	0.19164	0.04285

Table M - 3. Summary of correlations between IAT trust z-scores and post-task trust scores by condition

Condition	***Correlation with IAT z-score***	***Significance***
TT+TC	-.034	.84
AT+TC	-.046	.78
TT+UC	-.074	.65
AT+UC	.106	.52

Table M - 4. Descriptive statistics for post-task trust scores by experimental conditions and IAT order

IAT Order	***Communication Pattern***	***Transparency***	***N***	***M***	***SD***	***SE***
Automation + Good	Transactional	Team	21	62.0000	7.37564	1.861
		Agent		61.5789	9.65123	1.983
	Unidirectional	Team		61.8000	8.42219	1.940
		Agent		61.0952	9.29465	1.978
Automation + Bad	Transactional	Team	19	61.5789	9.65123	1.983
		Agent		61.8000	8.42219	1.940
	Unidirectional	Team		61.0952	9.29465	1.978
		Agent		61.4737	8.85292	1.957

APPENDIX N: **GODSPEED QUESTIONNAIRE SERIES DESCRIPTIVE STATISTICS TABLES**

Table N - 1. Descriptive statistics for overall Anthropomorphism scores by experimental conditions

Condition	***N***	***M***	***SD***	***SE***
TT+TC	40	2.4100	0.71173	0.113
AT+TC	40	2.3850	0.75296	0.119
TT+UC	40	2.4300	0.71833	0.114
AT+UC	40	2.2500	0.72713	0.115

Table N - 2. Descriptive statistics for overall Animacy scores by experimental conditions

Condition	***N***	***M***	***SD***	***SE***
TT+TC	40	2.8583	0.53582	0.085
AT+TC	40	2.8708	0.74103	0.117
TT+UC	40	2.7417	0.71507	0.113
AT+UC	40	2.5917	0.78714	0.124

Table N - 3. Descriptive statistics for overall Likeability scores by experimental conditions

Condition	***N***	***M***	***SD***	***SE***
TT+TC	40	3.3850	0.53854	0.085
AT+TC	40	3.2650	0.65066	0.103
TT+UC	40	3.2200	0.61067	0.097
AT+UC	40	3.0600	0.78864	0.125

Table N - 4. Descriptive statistics for overall Perceived Intelligence scores by experimental conditions

Condition	***N***	***M***	***SD***	***SE***
TT+TC	40	3.930	0.52340	0.083
AT+TC	40	3.880	0.61235	0.097
TT+UC	40	3.760	0.74997	0.119
AT+UC	40	3.570	0.89046	0.141

Table N - 5. Descriptive statistics for overall Perceived Safety scores by experimental conditions

Condition	***N***	***M***	***SD***	***SE***
TT+TC	40	3.200	0.50524	0.080
AT+TC	40	3.200	0.48216	0.076
TT+UC	40	3.275	0.58901	0.093
AT+UC	40	3.200	0.41893	0.066

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