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THESIS

THIS IS MY ROBOT: THERE ARE MANY LIKE IT, BUT THIS ONE IS MINE

by

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June 2020

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13. ABSTRACT (maximum 200 words)

This study explored the interactions of machine learning (ML) and serious gaming on trust in the context of a manned-unmanned team. While the government commits immense capital to develop autonomous systems for our warfighters, they often go unused due to skepticism of their performance and reasoning. Complexity and cost of the systems create an atmosphere that is prohibitive to daily training. These factors foster mistrust in valuable systems that could otherwise aid the warfighter.

In our experiment, the influence of serious gaming and autonomous behavior development was field tested with 40 participants in a two-group dual-task paradigm design to measure choice, trust indicators, and secondary task performance (STP). In a serious game, the control group learned the capabilities of an autonomous ground vehicle (AGV), while the experimental group “trained” the behaviors of the AGV. The experimental group invested significantly more time in the serious game. During execution of a live AGV task, no significant differences of trust indicators or STP occurred between groups. Time in the serious game in combination with trends in the choice of autonomous or teleoperated control of the AGV may imply that users prefer a user-trained AGV over an off-the-shelf solution. All data points to the need for further studies into the use of serious gaming to develop autonomous behaviors through an interactive ML approach.

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THIS IS MY ROBOT: THERE ARE MANY LIKE IT, BUT THIS ONE IS MINE

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LIST OF ACRONYMS AND ABBREVIATIONS

AITB-E	Advanced Infantry Training Battalion – East
AI	artificial intelligence
aML	automatic machine learning
CMC	Commandant of the Marine Corps
CNA	Center for Naval Analysis
COA	course of action
COGLE	COmmon Ground Learning and Explanation
CPG	Commandant's Planning Guidance
CROWS	Common Remotely Operated Weapon Station
DARPA	Defense Advanced Research Projects Agency
DoD	Department of Defense
EMAV	Expeditionary Modular Autonomous Vehicle
E-MOUT	Enhanced-Military Operations in Urbanized Terrain
FMF	Fleet Marine Force
HMMWV	High Mobility Multi-Wheeled Vehicles
iML	interactive machine learning
ISR	intelligence surveillance reconnaissance
ITL	Interactive Task Learning
JAIC	Joint Artificial Intelligence Center
JLTV	Joint Light Tactical Vehicle
LOA	limited operational assessment
LVC-TE	Live, Virtual, and Constructive – Training Environment
MCWL	Marine Corps Warfighting Lab
M&S	modeling and simulations
ML	machine learning
MOUT	military operations in urbanized terrain
MUM-T	manned unmanned teaming
NPS	Naval Postgraduate School
S&T	science and technology
SBF	support by fire

SUGV	small unmanned ground vehicle
TDK	Tactical Decision Kit
UAV	unmanned aerial vehicle
UGV	unmanned ground vehicle
USMC	United States Marine Corps
WOZ	Wizard of Oz
XAI	explainable artificial intelligence

I. INTRODUCTION

There is a continuous commitment in terms of time and capital spent to develop autonomous systems that enhance tactical operations. However, autonomous systems that are designed to help the warfighter are useful only when the Marine trusts it. Trust is not automatically established, and in many cases, force-multiplying systems go unused due to the human's skepticism regarding its ability. Furthermore, as machines transition from teleoperated toward partially or fully automated, the capabilities, limitations, and reasoning of behaviors of the machines will be further mystified to the user. Additionally, the complexities, maintenance, and cost of future machines will create an environment that is prohibitive to daily real-world training in an infantry battalion. These two factors, inability to (a) understand artificial intelligence (AI) and (b) train daily, will compound to create an atmosphere of mistrust in valuable systems that could otherwise improve the lethality of Infantry Marines. The research will inform how trust transfers from a virtual environment to live execution for different levels of autonomy and AI, ranging from teleoperated, automatic machine learning (aML), and interactive machine learning (iML) robots.

A. BACKGROUND

As described in the 38th Commandant of the Marine Corps' Planning Guidance (CPG) [1], "The Marine Corps confronts an increasingly complex operational environment abroad and a challenging fiscal outlook" [1]. An element of this complex future is the advent and incorporation of AI and autonomous systems. The CPG states that these elements are changing the character of war. The Commandant of the Marine Corps' (CMC) number one priority is the force structure of the Marine Corps. He states, "We will divest of legacy defense programs and force structure that support legacy capabilities" [1]. Due to the CMC's predictions on autonomous systems and AI, and his willingness to invest in the right technologies, a continued increase in conversations, ideas, and advances will ensue. To aid in this thrust of strategic investments, a detailed list of considerations will be made for each system in development and how it will aid in the warfighter's lethality. Two key elements that subsume the considerations are trust and utilization.

In addition to the CPG, the Joint Operating Environment 2035 [2] provides a strong foundation for how this technology will influence the future:

> The next two decades will see significant advances in autonomy and machine learning, to include the emergence of robots working together in groups and as swarms. New and powerful robotic systems will be used to perform complex actions, make autonomous decisions, deliver lethal force, provide ISR [Intelligence, Surveillance, Reconnaissance] coverage, and speed response times over wider areas of the globe. [2]

This same document argues that robots will augment human capabilities and will serve as a force multiplier, thus increasing the overall lethality and performance of the unit [2].

These two strategic level concepts drive actions at the Marine Corps Warfighting Laboratory (MCWL). Though the 2018 USMC Science and Technology (S&T) Strategic Plan [3] predates the CPG, it is still prescient to the future operating environment that the CMC foresees. It has identified the following objective in Joint Capability Area 3 – Force Application as Maneuver S&T Objective-4: Advanced Robotic Systems in Support of Ground Maneuver. Guidance for this objective is:

> Develop affordable technologies to enhance effective and efficient employment of ground robotics. Focus on improving capabilities while reducing training and operating requirements of user Marines. Fully autonomous vehicles are not necessarily the goal. Technologies that enable effective 'supervised autonomy' by the Marine user, to include teleoperation, machine vision, perception, obstacle avoidance, convoy following, and the ability to self-navigate pre-planned routes are desired capabilities. [3]

It appears that this current strategic objective is within reach. In 2018, MCWL S&T Division led a Manned-Unmanned Teaming (MUM-T) Limited Operational Assessment (LOA) [4] at Muscatatuck Urban Training Center, Indiana. During this LOA, MCWL had success with the Expeditionary Modular Autonomous Vehicle (EMAV). As a tracked unmanned ground vehicle (UGV), it was equipped with a Common Remotely Operated Weapon Station, known as CROWS II, that mounted a .50 caliber machine gun. The operation of the overall system was the sole responsibility for two Marines, one for the machine gun – the other for the EMAV movements [4]. To build from these successes, one could anticipate that the next S&T Strategic guidance will read

> Develop affordable technologies to enhance effective and efficient employment of ground robotics. Focus on improving capabilities while reducing training and operating requirements of user Marines. Fully autonomous vehicles are *still* not the goal. Technologies that enable effective '*interdependence*' by the Marine user *and robot*, to include *teamed operations that exploit the capabilities of both the Marine and robot are desired. These technologies must seek to magnify the capabilities of the individual Marine, not merely allow him to conduct a similar task by dissimilar means.*

The successes of the EMAV by the Marines at Muscatatuck lay a solid foundation for getting the right tools in the hands the Marines. A fictional vignette of the future from the MCWL's S&T Strategic Plan [3] states, "Marines rely heavily upon machines functioning at varying levels of autonomy for precision fires, logistics, and [ISR] support" [3]. This guidance confirms the use of autonomous systems in our future and makes apparent that increasing the lethality of Marines via utilization and trust of the systems will be complementing factors.

From a previous infantry battalion operation's officer perspective [5], A hasty analysis of an infantry battalion's dwell cycle shows that they will spend approximately 80 out of 365 days in a field training environment [5]. To supplement this shortfall and build the required intimacy within small units, Marines currently conduct "back-yard" training—conducting patrolling operations within close proximity to their barracks. It is overly optimistic to think that future Marines will be operating daily with their robots around battalion headquarters. Maintenance, cost, durability, and garrison rules provide a stark reminder of the difficulties that impede daily training. A fitting example is the observation of the regularly filled motor pools that house 40+ High Mobility Multi-Wheeled Vehicles (HMMWV) parked neatly in a row, not being used in training or operations. The current way the United States Marine Corps (USMC) supplements HMMWV training is through the use of the Combat Convoy Simulator [6]. Many more examples of the use of simulations provide training where the live option is cost, time, and maintenance prohibitive.

A case study of the Joint Light Tactical Vehicle (JLTV), shows the USMC has improved in keeping simulators relevant to the newest gear in their inventory [7].

Additionally, it appears that industry is prepared to provide the simulators to support training when asked by the Army and Marines [8],[9]. While these are favorable signs, future equipment imbued with automation and AI, as directed in the above referenced strategic guidance, will require simulators as a planning factor in the systems engineering design process. Simulators will be valuable in the context of smaller systems like the EMAV. The Marine's experience with the system in a virtual environment will provide familiarity and training with the capabilities and limitations of the system.

The Marine Corps' future systems will have AI. The drivers of future robot actions will range from assisted teleoperation through AI machine learning (ML) code. As technological complexities increase the concept of trust becomes more complex—the technology is perceived to be more human-like and less machine-like. According to experts in the field of trust and automation, Lee and See [10], human trust in automation technologies ranging from teleoperation to ML AI needs to be better understood [10].

While the types and levels of autonomy and intelligence of future systems will vary, the mystifying nature of its decision process to the end-user will remain. This syndrome is commonly known as a "Black Box." The inability to explain the decision-making process of AI is a topic of great research among academics, as well as the Department of Defense (DoD).

The lead effort to help reduce the black box syndrome of AI within the DOD is the Explainable AI (XAI) program at the Defense Advanced Research Projects Agency (DARPA). DARPA's XAI [11] team is exploring over 15 different types of ML techniques, ranging from deep learning and neural nets to decision trees [11]. The line of their research focused on autonomous, intelligent robots and XAI.

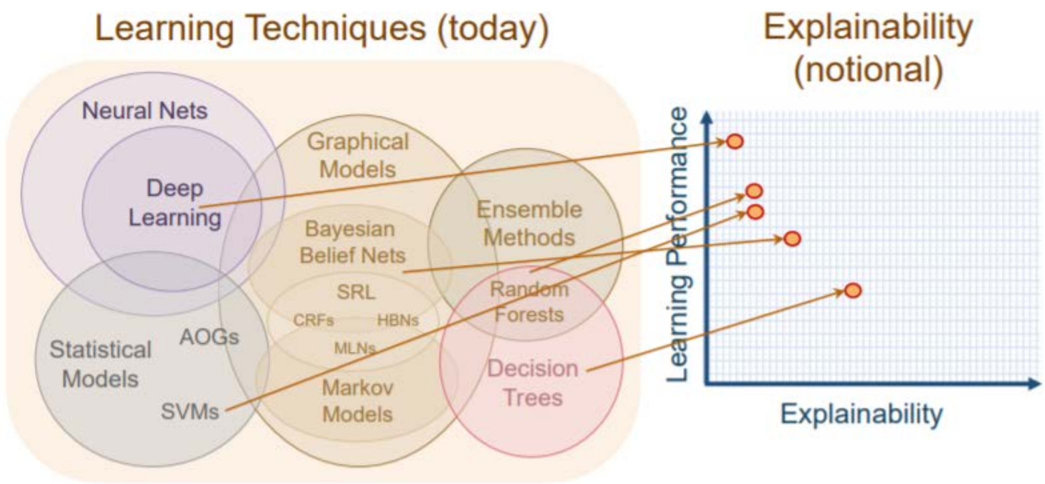

Figure 1. Current Machine Learning Techniques and Notional Explanability. Source: [11].

As Figure 1 shows, machines learn in myriad ways today. Analysis of Figure 1 reveals that neural networks are the smartest with the lowest explainability. Once the neural network is appropriately calibrated, it teaches itself the correct decisions through a comparison of the results achieved through a high amount repetitions to a desired result. Thus, its self-teaching creates a low explainability. Continuing, the decision trees with the highest explainability are programmed to create their code through parameterized situations for reciprocated decisions. This code is then readable; it increases its explainability. Additionally, to have an appropriate bedrock to begin a decision tree brain requires a large amount of complex hard coding of the autonomous actions. According to Amershi et al. [12], this requirement places a high demand of tight coupling between the programmer and warfighter to achieve the warfighter's desired outcome. This implies a lengthy design and implementation process due to the diverse nature of the programmer and end user. Each requires the other's expertise to create an effective autonomous system [12]. A proposed way to generate tighter coupling is to place the warfighter closer to the coding. iML in a virtual environment is a viable option to answer the problems listed below.

B. PROBLEM STATEMENT

Current approaches to the development of autonomous systems for Marine Corps Infantry community do not account for the following:

- Implementing MUM-T into a USMC Infantry Battalion environment
- Fielding simulation systems with the production of near equipment to include MUM-T systems
- Designing and enabling military simulations to allow for ML techniques
- Achieving the full potential of autonomous actions with current systems
- Explaining actions of a system developed by aML are difficult.

When compounded or alone, the aforementioned list of shortfalls will degrade the trust and utilization of valuable systems.

C. OBJECTIVES

The primary objective of this research is to understand how autonomy and ML techniques influence the development of trust in virtual environments for MUM-T systems. Secondary objectives are to explore AI, autonomy, automation, and their interactions. For AI, to understand different techniques for ML to create more explainable AI. The XAI drives towards the usage of serious games within virtual environments and how they are currently used for robotic movements and ML. The final secondary objective is to explore MUM-T interactions and how trust is developed, maintained, and calibrated within the team.

This research will assist in the Marine Corps' movement towards its MUM-T goals by demonstrating an approach to measure and understand the transfer of trust from a virtual gaming environment to live execution. For the aim of more explainable AI, the thesis will lay a baseline for the employment of iML techniques. Finally, this thesis will close by showing a conceptual model for future employment of MUM-T ground systems within a Marine Corps' Infantry Battalion.

Though a motivation for the research is the implementation of ML outputs into current virtual environment gaming and simulations, neither gaming, simulations, nor ML input or output requirements will be explored in this thesis. Also, the topics of game fidelity within graphics and physics modeling, and user-interface for gaming and robotics will not be covered. These elements could have a great impact on the development of trust but will remain constant for all iterations of the experiment to ensure their impact will be negligible.

D. RESEARCH QUESTIONS

1. How is the transfer of trust from a virtual environment to live execution and utilization of an unmanned autonomous robot influenced by the types of machine learning for the autonomous actions?

2. How is the attention on a primary task of a Marine reduced by teaming with an aML and iML robot?

E. THESIS DESIGN

To fully cover this topic, problem, and research questions, the thesis will establish definitions and explore research in the areas of AI, MUM-T, and trust throughout Chapter II. With the context, definitions, and surrounding research developed in Chapters I–II, allows for the detailed explanation of the experiment in Chapter III. The following chapter presents the results from the experiment. Finally, Chapter V describes the conclusions, and the author’s conceptual model for the use of MUM-T in a USMC Infantry Battalion.

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II. LITERATURE REVIEW

A. OVERVIEW

This chapter will provide a contextual framework, define concepts, and review works that directly influence or explore the same topics as this research. Academic surveys, textbooks, and published DoD reports were used to build each definition and show what is in the realm of possible for simulations, AI, autonomy, ML, and MUM-T.

B. USE OF SIMULATIONS

1. Simulations in the USMC

According to a Center for Naval Analysis (CNA) report [13], the DoD has used simulators to aid in the training of its pilots since the 1950s. Ever since then, the DoD continued to seek improvements in simulations and simulators to decrease cost and time for training. Though the air community has adopted simulations and simulators more rapidly than ground forces, great strides are being made by the ground community to incorporate simulators into the training regimen. Recent advances in simulators for ground forces are vast, and, as shown in Figure 2, ranging from training division and higher staffs for planning and decision-making processes to an infantry squad in an immersive environment. Simulators can be computer-based simulations to force-on-force actions with simulated munitions. These simulations and simulators aid in the training of individuals and different unit sizes. The training aids in battle drill execution, decision making, and unit cohesion [13].

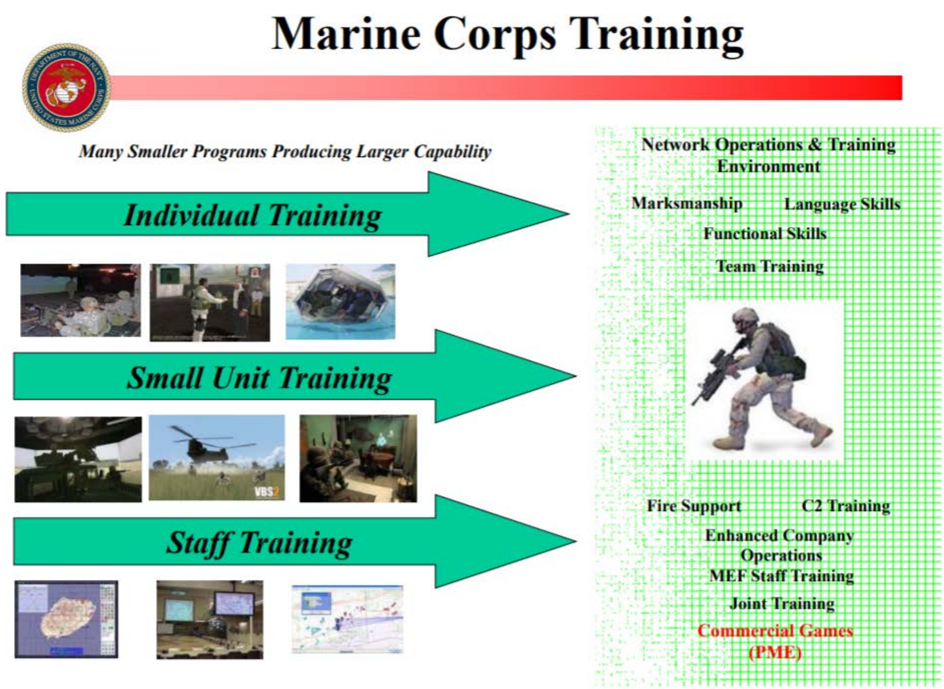


Figure 2. Overview of USMC Simulations for Training. Source: [14].

Even with this momentum for ground forces, the CNA [13] conducted a comprehensive use of the USMC's use of simulations for ground force training in 2009. The report concluded that the USMC did not currently use simulations in a coherent or standardized manner but had a suitable and appropriate master plan in the Marine Corps Training and Education Command's U.S. Marine Corps Training Modeling and Simulation Master Plan. The plan [15] incorporates and maximizes the use of training simulations to more efficiently utilize scarce resources [15]. The premise to the identified end-state of the master plan falls in line with motivations of this research. The motivations read:

> This end-state represents a ground force that is able to use technologies now and in the years to come to both improve the quality of its training program and to address budget constraints via training that requires fewer resources. It assumes that limitations to funding, resources, and time, as well as safety concerns, will reduce the amount of training that can be conducted in a live-fire environment; thus, non-live-fire training options are desirable. [13]

The identified end-states of the master plan have simulations addressing shortfalls in training and capabilities, allowing for progressive training, and used throughout the force [15]. The CNA identifies one of the two ways to achieve the presented end-state by:

> Appropriate development of future training systems and associated M&S [Modeling & Simulations] technologies. For future acquisitions, the Marine Corps can best achieve its desired end-state by developing those training systems that either address significant gaps in currently fielded systems or achieve the greatest benefit to training capability. [13]

Though it may not require mentioning, the CNA study is absent on the guidance for requisition of simulations to pair with emerging technologies to prevent significant gaps for systems that will be fielded in the future. The USMC S&T Master Plan answers this gap, "developing Marines to effectively operate in complexity by leveraging simulation capabilities, developing leaders at every echelon, emphasizing quality in leadership, and supporting cultural learning at all levels of operations" [3]. The long-term answer that is being developed within the USMC is the "Live, Virtual, Constructive – Training Environment (LVC-TE)." This will be a vast and diverse environment that will allow for training and exercises at the individual, unit, and collective levels [16].

The most recent squad-level simulators fielded to aid in unit cohesion and decision making are the Tactical Decision Kits (TDKs). The TDKs are currently fielded to each infantry battalion within the active duty Marine Corps. Through computer-based simulations an infantry squad can conduct interactive tactical decision games, play first-person shooter serious games, and utilize augmented reality to aid with spatial awareness for use of fires. According to a USMC brief [17], the TDK aids the user in the following:

- Rapid decision-making
- Tactics bred from competition
- Fighting a thinking enemy
- Training decisiveness [17]

These learning points are provided to the users through immediate review and feedback while leveraging the "generational strengths" [17] of the technically advanced Marines within the USMC. This same concept and training objectives will continue to be relevant as the Marine Corps continues to adopt MUM-T. Just as squad leaders train their

Marines through simulation-based training, there is the potential for Marines to train their partnered robot in the same fashion.

2. Simulations for Robotic Training

Humans are not the only trainee in a simulated environment; robotic programming can also be done in a simulated environment. According to Biggs and MacDonald [18], there are two main ways in which robotic programming occurs: manual or automatic. Manually programmed robots require the user and/or programmer to code the robot's program directly. An automatically programmed robot generates its program through the interactions between a robot and human. The second form, automatic programming, has come to the forefront as robots become more prevalent and users have less technical skills. This increases the ease of use and programming flexibility of the robots by the users. Both of these programming modes can be done in real-time or via a simulated environment [18].

Biggs and MacDonald state there are three categories, as shown in Figure 3, of automatic programming: Programming by Demonstration (PbD), Instructive Systems, and Learning Systems. PbD has been in use for many years, specifically for industrial robotics. The "Teach Pendant / Touch" style of PbD is where the user would move the robotic element and the program would record the input. For example, a user would manipulate a robotic arm to show where it could pick up an item for installation on an assembly line [18]. The Gesture/Voice/Vision elements is where the user would coach the robot into its actions via those input signals vice physically manipulating the robot. These input signals are then recorded and create the robotic automation. For instructive systems, the robot is given instructions by the user in real-time. This usually incorporates already programmed sequences of actions and allows the user to link them together to accomplish specific tasks [18]. Of interest to this thesis is the concept of a learning system that "creates a program by inductive inference from user-provided examples and self-exploration by the robot" [18]. This approach utilizes smart AI agents to control the actions. Some elements of the actions are taught to the agent by a user and then through ML techniques the robot explores how to improve those actions. According to multiple researchers: Bingham [19] and Wiggers [20], a majority of AI agent's exploration is done in a simulated environment to limit wear and tear on the robotic systems, and once efficient actions are learned, it is then transferred to the physical robot [19], [20].

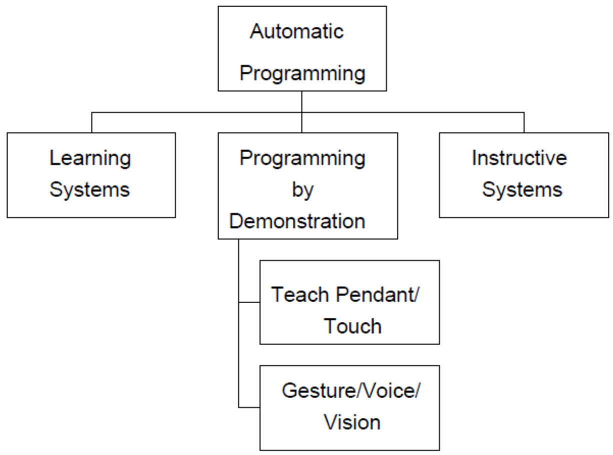


Figure 3. Categories of Automatic Robotic Programming. Source: [18].

3. Summary

Simulations are engrained training grounds for both U.S. Marines and AI driven robots. The Marine Corps is continuing to invest in the development of simulation training grounds for individual, small-unit, and staff training. The ability to partner a Marine with an AI agent in a virtual environment creates a robust opportunity for the Marine to develop an AI agent to perform tasks that can be transplanted into a robotic system.

C. ARTIFICIAL INTELLIGENCE, AUTONOMY, AND AUTOMATION

AI, autonomy, and automation have been areas of exploration and research since the 1950s. Still, after such a period, there is not a clear definition for AI nor autonomy [21],[22]. Though the field of research cannot decide on appropriate definitions, there are obvious benefits that AI, automation, and autonomy can provide to our daily lives in both civilian and military spectrums. The following sections will compare and contrast the academic, practitioner, and military perceptions of the word. The following sections yield that AI is the "ability of machines to perform tasks that normally require human intelligence…to include learning” [23]. For actions that have specific inputs to specific output, automation is used. For environments that require sensing and understanding a spectrum of inputs to achieve a goal-based output, autonomy is used.

1. Artificial Intelligence Defined

This section explores different approaches to defining what AI is. Definitions from leading textbooks, researchers, and the DoD are presented.

a. Russell and Norvig’s Approach

Formative work in the science of AI by Russell and Norvig [24], place useable definitions of AI developed by a multitude of respected researchers into four specific focus areas [24]. These areas are the categorization of human and rational actions and thought. Figure 4 is how Russell and Norvig binned the definitions. Within Figure 4, the rows of *thinking* and *acting* are categories used as the primary goals for the AI. Thinking is how to make the “brains” of the system work while actions are focused on the functions and behaviors of the system. *Humanly* and *rationally* are the depictions to characterize how a system performs [24].

Thinking Humanly "The exciting new effort to make computers think . . . *machines with minds,* in the full and literal sense." (Haugeland, 1985) "[The automation of] activities that we associate with human thinking, activities such as decision-making, problem solving, learning .. ." (Hellman, 1978)	**Thinking Rationally** "The study of mental faculties through the use of computational models." (Charniak and McDermott, 1985) "The study of the computations that make it possible to perceive, reason, and act." (Winston, 1992)
Acting Humanly "The art of creating machines that perform functions that require intelligence when performed by people." (Kurzweil, 1990) "The study of how to make computers do things at which, at the moment, people are better." (Rich and Knight, 1991)	**Acting Rationally** "Computational Intelligence is the study of the design of intelligent agents." (Poole *et at,* 1998) "AI . . . is concerned with intelligent behavior in artifacts." (Nilsson, 1998)

Figure 4. Binning of AI Definitions. Source: [24].

(1) Thinking Humanly

Cognitive sciences dominate this area of AI, which focuses on understanding how humans think and then making the AI mimic that process. The coupling of AI experts and cognitive scientists allow for growth and experimentation in both areas [24]. The AI scientists that focus in this realm believe that the AI should know the best answer, and if no right answer it possible in the uncertain situation then it should at least know the best answer [23]. Thinking as a human does not always imply that the thoughts will be rational.

(2) Thinking Rationally

The concept of rational thought is derived from the years of intellectual debate of great philosophers ranging from Socrates to Mills. This concept heavily utilizes the theory of logic. The deep use of logic creates difficulty for informal environments that cannot be distilled into a simple logic statement. In uncertain environments, an answer may not be achievable [24]. Additionally, this concept will never achieve a “good enough solution,” but will continue to hunt for the right answer.

(3) Acting Humanly

This focus area stemmed from the Turing Test developed by Alan Turing in 1950 [24]. The aim of the test was to have a person write a question and pass it behind a curtain. If the person was unable to discern if the answer that came back from the other side of the curtain was from a human or machine, then AI was achieved [25]. This test precludes on how the action was conceived. It could be either through rational or human process. This does assume that human actions are not perfect, but in some ways are predictable.

(4) Acting Rationally

Russel and Norvig favor the rational agent approach for two reasons. 1. It allows for more means to achieve rationality. 2. It has greater flexibility for exploration than attempting to achieve human behavior or thought. Since the exploration is not bound by human processing limitations, the agent can act in ways that act in the most optimal and rational manners. That being said, this area expects the AI to develop rational autonomous actions based off of learning and perceptions [24].

b. Other Academic Approaches

Singh et al. [21] provides a comprehensive list of other researchers' definitions of AI. As expected, most definitions presented fall into the bins created by [24]. The traits of AI that are synthesized from the analysis by [21] are "reasoning, knowledge, planning, learning, communication, perception and the ability to move and manipulate objects." Considering this comprehensive list of traits, a useable definition is also presented by [21] as, "AI is the branch of computer science which deals with intelligence of machines where an intelligent agent is a system that perceives its environment and takes actions which maximize its chances of success" [21]. Singh's et al. use of "agent" is stimulating and reckons to Russell and Norvig's favored approach to 'Acting Rationally.' Singh et al.'s approach to defining the principles of AI closely aligns to the DoD's definition.

c. DoD Approach

In 2018, the DoD established the Joint Artificial Intelligence Center (JAIC) with the aims to "enhance the ability for DoD components to execute new AI initiatives, experiment, and learn within a common framework" [26]. This guiding statement from the DoD encourages the DoD's components to take AI from conceptual research towards the execution of tangible experiments and implementation of AI. The DoD defines AI as "the ability of machines to perform tasks that normally require human intelligence—for example, recognizing patterns, learning from experience, drawing conclusions, making predictions, or taking action—whether digitally or as the smart software behind autonomous physical systems" [23]. This definition is very similar to the principles presented by [21]. An overarching connection is the "smart" or "intelligent" agent.

d. Summary

The main concepts brought to the forefront by Russell and Norvig provide a baseline for the common principles asserted by Singh et al. and the DoD. Each of the principles presented by [21] and [23] fall within one of the human/rational thinking/action from [24]. The commonality of AI practitioners' definitions allow for the implementation of those principles in a software or hardware-based agent. An agent is a "means or instrument by which a guiding intelligence achieves a result" [27]. With the agent taking on the following principles to guide its intelligence for tasks like recognize, learn, infer, predict, communicate, and take action, there is now a working aimpoint for what the agent must do to be AI. How it achieves those aimpoints, like a human or rationally, appears to be irrelevant to the DoD. The overarching nature of the DoD's definition allow for the development of the agent in any thought pattern and action type. This implies that the goal of the DoD is to not have a single AI solve all problems, but that there will be multiple AI agents developed as tools be used in different distinct challenge areas.

Of the many challenge areas defined by the DoD to utilize AI to solve problems, this thesis will focus on "Improving situational awareness and decision-making" [23]. The first thought comes to mind is the use of an AI robot teamed with an infantry squad. To help increase the efficiency and capabilities of the squad, there will be an expectation for the robot to conduct autonomous actions. To enable those actions AI is required. For this thesis, the DoD definition of AI will be used for "The ability of machines to perform tasks that normally require human intelligence—for example, recognizing patterns, learning from experience, drawing conclusions, making predictions, or taking action—whether digitally or as the smart software behind autonomous physical systems" [23].

2. Automation and Autonomy

As with the term AI, the use of autonomy and automation are flaunted virally as the solution to any challenging, monotonous, or dangerous task. Additionally, autonomy and automation are used interchangeably to describe similar systems, when they should not be. They are two different distinct types of systems—autonomous systems which has autonomy and automated systems which have automations. While all the conceptual end uses for the terms of autonomy and automation are usually appropriate, an understanding for each is required. The academic and military interpretations of autonomy and automation will be presented; and as expected, this section will result in a clear definition for automation and autonomy for use in this thesis.

a. Automation

Automation is the noun form of the word of automatic. According to Merriam-Webster [28], the origins of automatic break down to "self-acting" [28]. What is absent in the definition or root of the word is intelligence or the ability to learn. This is not a slight on automated processes; according to Hoff and Bashir [29], automation is used in every corner of the earth [29]—it can analyze, inform, decide, and, even, act [30]. In the year 2000, Parasuraman et al. [30] developed a concept of automation: “Machines, especially computers, are now capable of carrying out many functions that at one time could only be performed by humans. Machine execution of such functions—or automation—has also been extended to functions that humans do not wish to perform, or cannot perform as accurately or reliably as machines” [30]. This is very similar to the expectations of the Turing Test, but only for highly specified actions. Thomas Sheridan [31] from the Massachusetts Institute of Technology’s Man-Machine Systems Laboratory provides the best and most inclusive definition that will be used for this thesis. Sheridan states, “Automation is the automatically controlled operation of an apparatus, a process, or a system by mechanical or electronic devises that take the place of human organs of observation, decision, and effort” [31]. Comparing to this to the definition of AI, automation is a well-trained, dumb agent. The lack of the ability to learn, or have intelligence, is what distinguishes automation from being AI. Conversely, AI systems can have automation sub-components. The automated agent would be able to execute whatever specific task it was created to accomplish, no more, no less. The DoD Roadmap [32] aids in this line of thought with their description of automated systems, “[Automated systems] are governed by prescriptive rules that allow for no deviations” [32].

b. Autonomy

With the understanding that automated processes lack AI and ability for deviations, a logical inference would be autonomy possesses AI and can deviate. Only the latter is true. The origins of the word autonomy, which come from autonomous, means “something autonomous makes its own laws” [33]. The DoD Roadmap contrasts autonomy (i.e., autonomous systems) to automation. It states that “autonomous systems are governed by broad rules that allow the system to deviate from the baseline”[32]. The DoD Roadmap continues to define autonomy as “the ability of an entity to independently develop and select among different courses of action (COAs) to achieve goals based on the entity’s knowledge and understanding of the world, itself, and the situation” [32]. With the understanding that an entity represents the 'agent enabled machine,' this definition will be used for autonomy. This definition is reinforced by the Beer et al. [34]. Their definition is more explicit in the process of COA selection and interaction with the environment. They defined autonomy as "the extent to which a robot can **sense** its environment, **plan** based on that environment, and **act** upon that environment with the intent of reaching some **task-specific goal** (either given to or created by the robot) without external control" [34]. Of note from their definition is "the extent to which." This implies that there is a spectrum of autonomy "ranging from no autonomy to full autonomy" [34]. Figure 5 shows the wide variety of definitions for autonomy. Note that all allow for flexibility of the agent to interact with their environment.

Definitions of Agent and Robot Autonomy	
"The robot should be able to carry out its actions and to refine or modify the task and its own behavior according to the current goal and execution context of its task."	Alami et al., 1998, p. 316
"Autonomy refers to systems capable of operating in the real-world environment without any form of external control for extended periods of time."	Bekey, 2005, p. 1
"An autonomous agent is a system situated within and a part of an environment that sense that environment and acts on it, over time, in pursuit of its own agenda and so as to effect what it senses in the future;" "Exercises control over its own actions."	Franklin & Graesser, 1996, p. 25
"An Unmanned System's own ability of sensing, perceiving, analyzing, communicating, planning, decision-making, and acting, to achieve goals as assigned by its human operator(s) through designed HRI … The condition or quality of being self-governing."	Huang, 2004, p. 9
"'Function autonomously' indicates that the robot can operate, self-contained, under all reasonable conditions without requiring recourse to a human operator. Autonomy means that a robot can adapt to change in its environment (the lights get turned off) or itself (a part breaks) and continue to reach a goal."	Murphy, 2000, p. 4
"A rational agent should be autonomous—it should learn what it can to compensate for partial or incorrect prior knowledge."	Russell & Norvig, 2003, p. 37
"Autonomy refers to a robot's ability to accommodate variations in its environment. Different robots exhibit different degrees of autonomy; the degree of autonomy is often measured by relating the degree at which the environment can be varied to the mean time between failures, and other factors indicative of robot performance."	Thrun, 2004, p. 14
"Autonomy: agents operate without the direct intervention of humans or others, and have some kind of control over their actions and internal states."	Wooldridge & Jennings, 1995, p. 116

Of note, only Russell and Norvig mention learning in their definition.

Figure 5. Definitions for Agent and Robot Autonomy. Source: [30].

3. Summary

Automation is designed for specific inputs to result in specific outputs. Autonomy is designed for a broad spectrum of inputs to result in a task-specific goal. There is the possibility for an autonomous system to have automated actions as a sub-component. Autonomous systems that continue to learn and recognize patterns have AI agents powering their decision and action making. AI agents maintain the ability to write new "rules" for its decision-making process. With an understanding of AI, automation, and autonomy, the next step is to understand how an agent's ability to sense, plan, and act are created to allow for autonomous actions either in the virtual or real world.

D. MACHINE LEARNING

One could expect the title of this section to be "Agent Learning," because the main concern is how the agent, inside the machine, learns. The concept of the agent has been developed within this thesis to have a range of capability and intelligence. Within automated system it is well trained for execution with no capability of decision making, with autonomous systems it can make decisions within a finite space of inputs and outputs, and, finally, there are some AI systems that possess the ability to learn from experiences. According to Russell and Norvig, there are four different types of AI agents: Simple Reflex, Model-Based Reflex, Goal-Based, and Utility-Based [24]. An overly simplistic explanation of each follow:

- Simple Reflex – *If* agent perceives x *then* the agent does y. The agent has no memory.
- Model-Based Reflex – The agent can remember what has been done and builds a mental model. Based on the model's current condition it decides to do x, y, or z.
- Goal-Based – The agent can build a mental model of the current situation. It also knows what the goal model is. Based off the current model and goal model, the agent decides an action.
- Utility-Based – The agent can build a mental model of the current situation. It also knows what the goal model is. The agent also knows there's more than one way to achieve the goal model. The agent decides one the "best" action to achieve the goal model. [24]

This explanation helps us understand how agents work within an environment. Each of the agent types to follow maintain the capability to learn. For an agent to learn there are four fundamental sub-elements: Critic, Learning Element, Performance Element, and Problem Generator [24]. The interactions of each of these elements is shown in Figure 6.

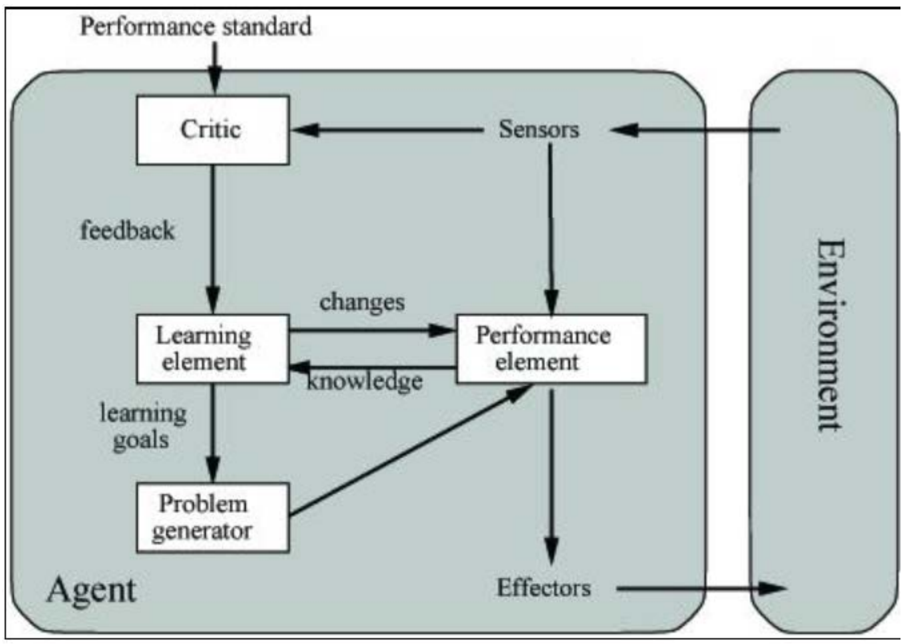


Figure 6. General Model of Learning Agents. Source: [24].

In reference to Figure 6, the *performance element* is what has been referred to as the agents listed above, the element that made the decisions on what to do for the entire system. The performance element still does that decision making. As we build elements to the agent, the learning enabled agent has the learning element and problem generator; additionally, the learning enabled agent is an alter-ego named the "critic." The *critic* is responsible for understanding what the correct result for the agent should be and providing feedback to the agent on how well of a job the agent did in contrast to the correct result. This feedback, or difference, is provided to the learning element. The *learning element* remembers the difference between the best result from the critic and what the performance element executed. The *problem generator* is the creativity element to the agent. The problem generator creates new ideas for exploration and experimentation to improve the agent's performance. Increasing the amount of creativity allowed for the agent, increases the number of attempts for originality by the agent [24]. The understanding of these internal interactions of the agent is critical for the explanation of different types of agent learning occurs.

1. Classifications of Machine Learning

The different components of the agent, i.e., critic, learning element, or performance generator, can learn. The learning of these components is enabled by what the agent already knows, how it prioritizes elements of the model, and what feedback should be used to learn [24]. The way that machine learning is classified is by the type of feedback that the critic provides. There are three major types of machine learning: Unsupervised, Supervised, and Reinforcement Machine Learning [24]. The types of learning and performance elements, i.e., neural networks and decision trees, can be applied across the types of learning methods. For the explanation of types of learning, the categorization of photos will be used as a simple use case. Each section will also discuss if novel machine learning occurs. Novel machine learning is when the computer presents results that are successful but have not been thought of by humans.

a. Unsupervised Machine Learning

Unsupervised machine learning provides minimal guidance to the critic. In turn, the critic provides no explicit feedback to the agent. This sort of machine learning process is best suited for pattern matching or clustering. With a large amount of data iterations, i.e., 100,000 photos, for the input, the agent learns to group the photos into different piles [24]. Once the bins are created, naming of the bins by the human is stilled required. This approach allows for novel exploration or binning by the agent. Elements may be within the photos that were hidden to the human eye that aid in different types of classifications.

b. Supervised Machine Learning

Supervised Machine Learning requires a clean set of sorted data for the initial learning to take place. With this type of learning, the right answer is provided directly to the agent after it is seen [24]. For example, as each of the 100,000 photos is shown to the system, the correct answer is also provided to the agent as to which bin the photo should be placed. This sort of learning requires a substantial amount of correct data, usually computed by a human previously, and prevents the novel explorations that is achievable by machine learning.

c. Reinforcement Machine Learning

Reinforcement Machine Learning provides a reward, either negative or positive, to the agent after a set amount of iterations or actions. The reward is decided by the critic based on the comparison of the performance element output compared to the ideal modeled outcome [24]. With the pictures as an example, a reward can be provided after every photo. The critic knew the picture was a cat, but the performance element classified the photo as a zebra, in turn a negative reward is administered. As expected, if the cat is classified as a cat, a positive reward is given. As the number of iterations between reward is increased, the flexibility for novel machine learning solutions to emerge is possible.

2. Explainability of Machine Learning

Machine learning has made great strides in recent years. Success stems from the implementation of different algorithms for the learning and performance elements of the agent and advances in computer speeds. One of the most recent examples of successful machine reinforcement learning is the work done by *DeepMind* and *Blizzard* with the StarCraft II Learning environment. StarCraft II is a real-time strategy game that involves the need for planning and execution of tasks [35]. With deep machine learning—millions of repetitions of the learning cycle—the team created a StarCraft II controller, named AlphaStar, that was able to defeat top-performing human players. During the premiere of AlphaStar's capability against the top StarCraft II players, AlphaStar's performance was indistinguishable from a human's, but justification for the moves and strategies performed were unable to be explained by any members of the team, onlookers, or AlphaStar [36]. This sort of superb performance from a "Black Box" is common characteristic for AI agents. AI's recent rapid growth and the "Black Box" syndrome has sparked a line of research and efforts along *Explainable* or *Interpretable Artificial Intelligence* [37].

a. *Justification for Explainable AI*

In *Peeking Inside the Black-Box: A Survey on Explainable Artificial Intelligence (XAI),* Adadi and Berrada [37] have identified four main reasons for the need of XAI: Explain to Justify, Explain to Control, Explain to Improve, and Explain to Discover [37]. Justification, control, and improvement are the primary concerns of this thesis. Discovering is focused on the human learning from the novel approaches learned by the AI during its machine learning processes. As this thesis will explore in Section II.F.3.a, justification, control, and system improvement will influence trust. 'Explain to justify' means that the AI can provide backing to the purpose of the decisions that were made. To an end-user in our case, a U.S. Marine, justification beyond simple logic coding is required – interpretable information on why an agent's decision occurred is needed. 'Explain to control' enables the AI agent to be a teammate controlled by the Marine. This will help with the rapid identification and adjustment of shortcomings [37]. 'Explain to improve' allows for the Marine to continue to improve the system as the Marine becomes more intimate with the AI agent's decision making processes [37]. These cases for explanation will allow for the improvement of the AI agent as a teammate for operations but does not help for the understanding of why AI is unexplainable.

b. *What Makes AI Un-explainable?*

The root of the inexplicable nature of AI stems from the machine learning models and the inability to "open-up" the learning and performance elements of the AI agent. DARPA's XAI program states that "machine learning models are opaque, non-intuitive, and difficult for people to understand" [11]. The models represent how the AI agent interprets the input to create its output. These models are created by algorithms that are represented within neural nets, Bayesian Belief nets, and various other techniques [11]. Even with the best computer scientists, the explanation of the calibration and adjustment of these models are inexplicable [38]—one cannot simply open the model and dissect it like a combustion engine.

As motivations and promises of AI increase, so does the research effort in making it explainable [11], [37]. Until this point in the thesis, the machine learning process are automatic, thus, automatic Machine Learning (aML). The agents learn through a large amount of pre-computed inputs and outputs. A line of DARPA research focused on autonomous, intelligent robots, and XAI is trending towards the use of interactive machine learning (iML) [11].

E. EXPLAINABLE ARTIFICIAL INTELLIGENCE (XAI)

1. Academic Review of XAI

With the speed and growth of AI partnered with its requirement to be understood, a substantial amount of research on XAI has followed. In December 2019, Arrieta et al. [39] created a survey of XAI concepts and taxonomies surrounding the topic. They reviewed over 400 scholarly articles and publications on XAI. Out of those reviews, the authors created a list of attributes for the motivations for XAI ranging from trustworthiness to privacy awareness. The attributes are listed in left most column of Table 1. Two critical motivations are interactivity and trustworthiness. Arrieta et al. connect these two motivations as important to “users affected by AI agent model decisions” [39]. Interactivity, trustworthiness, and user interactions are of importance to this work. In the case of this thesis, it is considered that U.S. Marines are the end-users and the AI agent developed through ML is running the robot that is a teammate to the U.S. Marine. The importance of trustworthiness and interactivity within a MUM-T are outlined within Section F. Manned-Unmanned Teaming (MUM-T).

Building from the concepts and algorithms that create the underlying structures for ML AI agents outlined in Section II.D. Machine Learning, Arrieta et al. research shows that the different types of AI agent model structure have varying levels and approaches to explainability, shown in Table 2 [39]. The “Transparent ML Models” are of interest due to their transparency to the end-user. This implies that the models are easily shown in a text or graphical format for the user to understand. An example of a “Transparent ML Model” is the decision tree model. Figure 7 shows a simple representation of how the decision tree model can be presented to the end user. Though this is a representation of relatively transparent AI model, to our Marines the training dataset that is developed through the ML process can still remain a black-box and/or the outputs are not the desired actions by the

Marine for their approach to "interactivity" with the unmanned teammate. A known shortfall for the transparent models, shown in Table 2, is that they lack the ability to have a large data set, knowledge base, within the agent's model. Thus, a majority of the work being completed on improving the explainability of AI is focused on the ML techniques that require the post-hoc analysis [39].

Table 1. XAI and Target Audiences. Source: [39].

XAI Goal	Main target audience (Fig. 2)	References
Trustworthiness	Domain experts, users of the model affected by decisions	[5, 10, 24, 32, 33, 34, 35, 36, 37]
Causality	Domain experts, managers and executive board members, regulatory entities/agencies	[35, 38, 39, 40, 41, 42, 43]
Transferability	Domain experts, data scientists	[5, 44, 21, 26, 45, 30, 32, 37, 38, 39, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85]
Informativeness	All	[5, 44, 21, 25, 26, 45, 30, 32, 34, 35, 37, 38, 41, 46, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 63, 64, 65, 66, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 86, 87, 88, 89, 59, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100, 101, 102, 103, 104, 105, 106, 107, 108, 109, 110, 111, 112, 113, 114, 115, 116, 117, 118, 119, 120, 121, 122, 123, 124, 125, 126, 127, 128, 129, 130, 131, 132, 133, 134, 135, 136, 137, 138, 139, 140, 141, 142, 143, 144, 145, 146, 147, 148, 149, 150, 151, 152, 153, 154]
Confidence	Domain experts, developers, managers, regulatory entities/agencies	[5, 45, 35, 46, 48, 54, 61, 72, 88, 89, 96, 108, 117, 119, 155]
Fairness	Users affected by model decisions, regulatory entities/agencies	[5, 24, 45, 35, 47, 99, 100, 101, 120, 121, 128, 156, 157, 158]
Accessibility	Product owners, managers, users affected by model decisions	[21, 26, 30, 32, 37, 50, 53, 55, 62, 67, 68, 69, 70, 71, 74, 75, 76, 86, 93, 94, 103, 105, 107, 108, 111, 112, 113, 114, 115, 124, 129]
Interactivity	Domain experts, users affected by model decisions	[37, 50, 59, 65, 67, 74, 86, 124]
Privacy awareness	Users affected by model decisions, regulatory entities/agencies	[89]

Table 2. Classification of ML Models to Explainability Source: [39].

Model	Transparent ML Models			Post-hoc analysis
	Simulatability	Decomposability	Algorithmic Transparency	
Linear/Logistic Regression	Predictors are human readable and interactions among them are kept to a minimum	Variables are still readable, but the number of interactions and predictors involved in them have grown to force decomposition	Variables and interactions are too complex to be analyzed without mathematical tools	Not needed
Decision Trees	A human can simulate and obtain the prediction of a decision tree on his/her own, without requiring any mathematical background	The model comprises rules that do not alter data whatsoever, and preserves their readability	Human-readable rules that explain the knowledge learned from data and allows for a direct understanding of the prediction process	Not needed
K-Nearest Neighbors	The complexity of the model (number of variables, their understandability and the similarity measure under use) matches human naive capabilities for simulation	The amount of variables is too high and/or the similarity measure is too complex to be able to simulate the model completely, but the similarity measure and the set of variables can be decomposed and analyzed separately	The similarity measure cannot be decomposed and/or the number of variables is so high that the user has to rely on mathematical and statistical tools to analyze the model	Not needed
Rule Based Learners	Variables included in rules are readable, and the size of the rule set is manageable by a human user without external help	The size of the rule set becomes too large to be analyzed without decomposing it into small rule chunks	Rules have become so complicated (and the rule set size has grown so much) that mathematical tools are needed for inspecting the model behaviour	Not needed
General Additive Models	Variables and the interaction among them as per the smooth functions involved in the model must be constrained within human capabilities for understanding	Interactions become too complex to be simulated, so decomposition techniques are required for analyzing the model	Due to their complexity, variables and interactions cannot be analyzed without the application of mathematical and statistical tools	Not needed
Bayesian Models	Statistical relationships modeled among variables and the variables themselves should be directly understandable by the target audience	Statistical relationships involve so many variables that they must be decomposed in marginals so as to ease their analysis	Statistical relationships cannot be interpreted even if already decomposed, and predictors are so complex that model can be only analyzed with mathematical tools	Not needed
Tree Ensembles	✗	✗	✗	Needed: Usually *Model simplification* or *Feature relevance* techniques
Support Vector Machines	✗	✗	✗	Needed: Usually *Model simplification* or *Local explanations* techniques
Multi–layer Neural Network	✗	✗	✗	Needed: Usually *Model simplification*, *Feature relevance* or *Visualization* techniques
Convolutional Neural Network	✗	✗	✗	Needed: Usually *Feature relevance* or *Visualization* techniques
Recurrent Neural Network	✗	✗	✗	Needed: Usually *Feature relevance* techniques

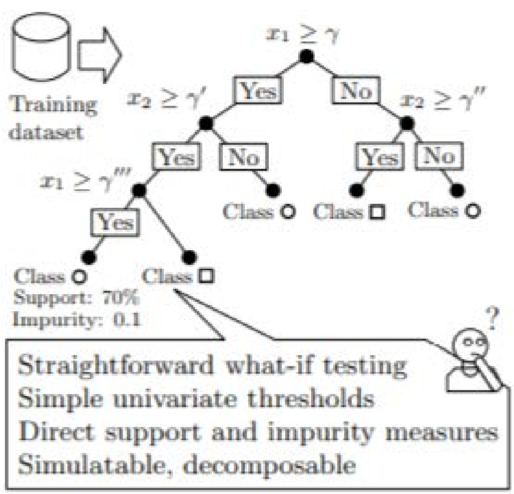


Figure 7. Illustration of Decision Tree Model. Source: [39].

As work continues for all types of ML models to increase the explainability, concerns still exist from the end-user having to conform to the agent's model and the data sets and algorithms used to create the agent's behaviors. There is still greater need to include the end-user in the development of the agent's model. This incorporation of the end-user will increase the user's understanding of the process, purpose, and capabilities of the agent's behavior.

2. User-Focused Proactive XAI Techniques

Building on the literature review conducted by Arrieta et al., the list of references presented in the "interactivity" and "trustworthiness" categories Table 1 were reviewed. Out of the 16 publications, only 2 focus on incorporating the user in a proactive approach to explaining the AI. A summarization of those two publications follow.

Utilizing the same metaphor as Alan Cooper does in his book '*The Inmates are Running the Asylum: Why High-Tech Products Drive Us Crazy and How to Restore the Sanity*;' Tim Miller et al. [40] argue that AI researchers are focused on developing explanatory agents for AI researchers, and not for the intended end-user. In Miller et al.'s self-proclaimed "light" literature review of XAI papers submitted for the International Joint Conference on AI of 2017, "almost all of the [twenty-three] papers were describing methods for automatically generating explanations of some type" [40]. Their brief survey of articles concludes that AI researchers must collaborate with researchers "from the social and behavioral sciences, to inform both model design and human behavioral experiments"[40]. Miller et al. confirm that the current approaches being taking by the DARPA XAI program for human-in-the-loop techniques of ML is the correct direction [40].

Zhang et al. [41] connects the concepts delivered by Miller et al. and confirms a critical factor for the development of the AI agent's model is its interpretability to the user. This interpretability builds expectations by the user of the robot's capabilities. The process used by Zhang et al. is to have an AI agent in a simulated environment execute a series of actions to complete a task. After the action is completed, the actions performed are collected under a term or label provided by a human. The example used by Zhang et al., takes basic movements of a robot and subsets them together under human labeling. The scenario involves a robot moving about a gridded space with the overall goal of collecting and storing boxes. At the primitive level, the robot can *move*, *observe*, *load*, and *unload*.

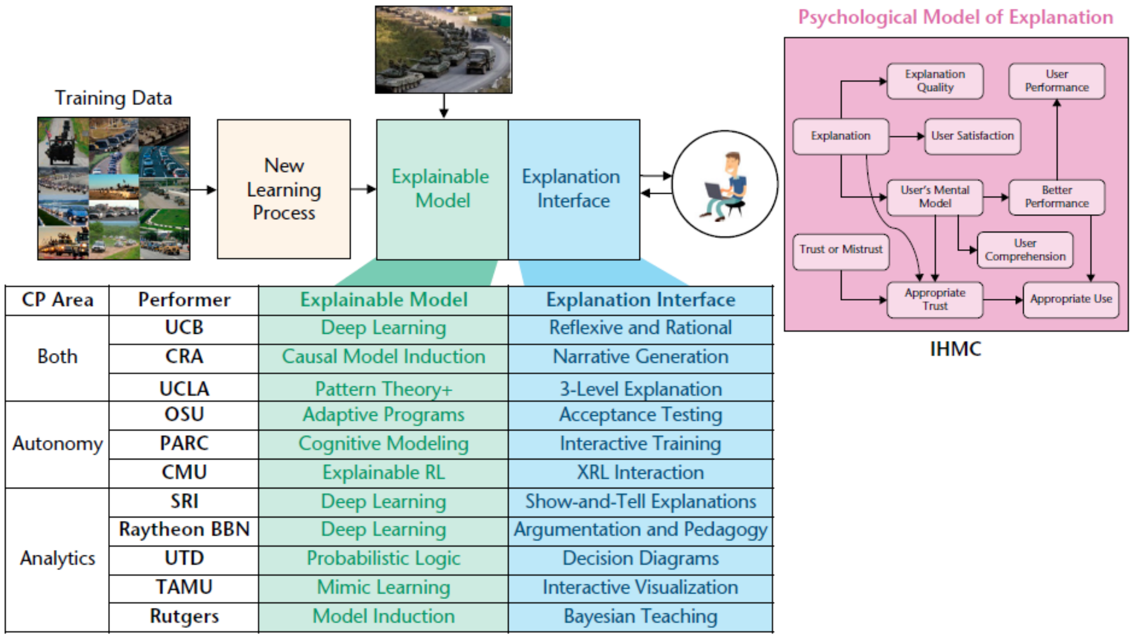
The user can collect these primitives into a higher-level task of *collect* which involves moving, observing, and loading the desired box. They call this process the human interpretation of training examples. Zhang et al. experimented with this process with 13 human subjects, a robot, and the standard task of block stacking. While comparing their process that allows for human labeling against a cost-optimal planner, they concluded that their process increases explainability and predictability of the robotic actions. In this context, the cost-optimal planner is like a "black-box" since it does not provide any explanation. The human labeling planner accounts for the user in its planning process and increases the explainability and predictability. In relationship to this thesis, the cost optimal planner is similar to an aML developed AI agent, while the human labeling planner is similar to iML[41]. The notion of predictability pairs well for trust and MUM-T.

3. DARPA Research

In addition to the academic realm, the DoD has taken great interest in the explainability of AI. In 2019, David Gunning, program manager in DARPA's Information Innovation Office, and David W. Aha [42], acting director of the U.S. Naval Research Laboratory's Navy Center for Applied Research in AI, summarized the efforts and purpose of the DARPA XAI program. They confirmed that XAI is essential for users to "understand, appropriately trust, and effectively manage these artificially intelligent partners" [42]. Gunning and Aha succinctly develop the concept of focusing on the user with three research questions: "(1) how to produce more explainable models, (2) how to design explanation interfaces, and (3) how to understand the psychologic requirements for effective explanations" [42]. The first two questions are covered by 11 XAI research teams. The research effort spans the lines for data analytics and autonomous systems. Of the 11 research teams, 3 are focused on autonomy, as shown in Figure 8.

Oregon State University (OSU) is focused on the user interfaces and the best approach for explaining actions by the autonomous system. Carnegie Mellon University (CMU) is creating a form of explainable reinforcement ML that explains why specific rewards were given to the agent while training. Of most importance to this thesis, Palo Alto Research Center (PARC) [43]; assisted by researchers from CMU, the Army Cyber

Institute, the University of Edinburgh, and the University of Michigan; "is developing an interactive sensemaking system that can explain the learned capabilities of an XAI system that controls a simulated unmanned aerial system (UAS)"[43].



CP Area	Performer	Explainable Model	Explanation Interface
Both	UCB	Deep Learning	Reflexive and Rational
	CRA	Causal Model Induction	Narrative Generation
	UCLA	Pattern Theory+	3-Level Explanation
Autonomy	OSU	Adaptive Programs	Acceptance Testing
	PARC	Cognitive Modeling	Interactive Training
	CMU	Explainable RL	XRL Interaction
Analytics	SRI	Deep Learning	Show-and-Tell Explanations
	Raytheon BBN	Deep Learning	Argumentation and Pedagogy
	UTD	Probabilistic Logic	Decision Diagrams
	TAMU	Mimic Learning	Interactive Visualization
	Rutgers	Model Induction	Bayesian Teaching

Figure 8. DARPA XAI Research Teams. Source: [42].

The tool PARC will utilize is an output of the COmmon Ground Learning and Explanation (COGLE) project. The COGLE tool "will support user sensemaking of autonomous system decisions, enable users to understand autonomous system strengths and weaknesses, convey an understanding of how the system will behave in the future, and provide ways for the user to improve the UAS's performance" [43]. As implied within the name of the project, the goal is to develop common ground for the user and the autonomous system. Within COGLE this is done through a virtual environment. The common ground will be built through human and computer interactions through demonstrations and explorations within the virtual environment. They anticipate that "human plus computer teams with common ground to work better and learn faster than humans or machines alone"

[43]. As is common practice in reinforcement learning, the AI agent will be placed through a curriculum of courses to develop its intelligence. The curriculum is shown in Figure 9.

Figure 9. COGLE's curriculum for the UAS training. Source: [43].

Since it is in a virtual environment, the end-user can observe the actions, interactions, and development of the intelligence during the reinforcement learning iterations. Additionally, and enabled through the user interface, the AI agent can provide explanation to the user, and the user can guide AI agent actions. These actions develop common ground with the user as a teacher and the AI agent as a student. PARC has termed this environment in the following way: "In analogy with pedagogy, we call this two-way human-in-the-loop partnership 'mechagogy' in analogy with pedagogy" [43]. Thus far, their research maximizes both the teacher's and student's qualities. Since the user is familiar with the contextual training scenario in the virtual environment, the user can guide the AI agent in the correct direction for learning; and due to the reinforcement learning nature of the AI agent, the AI agent can still produce novel results that can be shown to the user [43]. Though there are no published results of this project to include the topic of trust, it is expected that the common ground between user and AI agent will aid in the calibration of trust.

4. Interactive Machine Learning

Amershi et al. [12] state, iML is the intimate involvement of the end-user in the incremental development of the agent's model and its behavior [12]. iML is best explained through a comparison to aML. Figure 10 is a graphical comparison. The major difference between the aML and iML is when and how often the end-user interacts in the education process of the agent. In historical applications of aML, a ML expert would code and tweak the parameters for the ML process to educate the agent. This completed agent would then be presented to the end-user. At this point, the end-user has little awareness of the process used to create the agent, creating a low explainability of the agent for the end-user. Any gaps in the agent's model identified by the end-user would then require the ML expert's assistance in re-educating the agent. iML now pulls the end-user closer into the development of the agent. After the ML expert creates the appropriate paraments for the agent's educational success, the ML expert is no longer needed. The system established by the ML expert establishes the end-user as the critic for the agent's development. This increased involvement of the end-user in the development of the agent aids with the explainability [12].

Within iML, the human can fulfill the responsibility of the critic in both reinforcement ML, as with the thumbs up and down within Pandora Music and Podcast Application [12], or as the input of the "right answer" in supervised machine learning, as Gutzwiller and Reeder [44] explored for autonomous search and rescue patterns. Brown et al. [45], show that the iML AI agents can build a model for the specific user it is interacting with and present information in back to the user in a personalized manner, Figure 11. Additionally, Figure 11 demonstrates how the user can interact with the variety of ML processes; the format shown matches the standard view of AI agent development presented by Russell and Norvig in Figure 6.

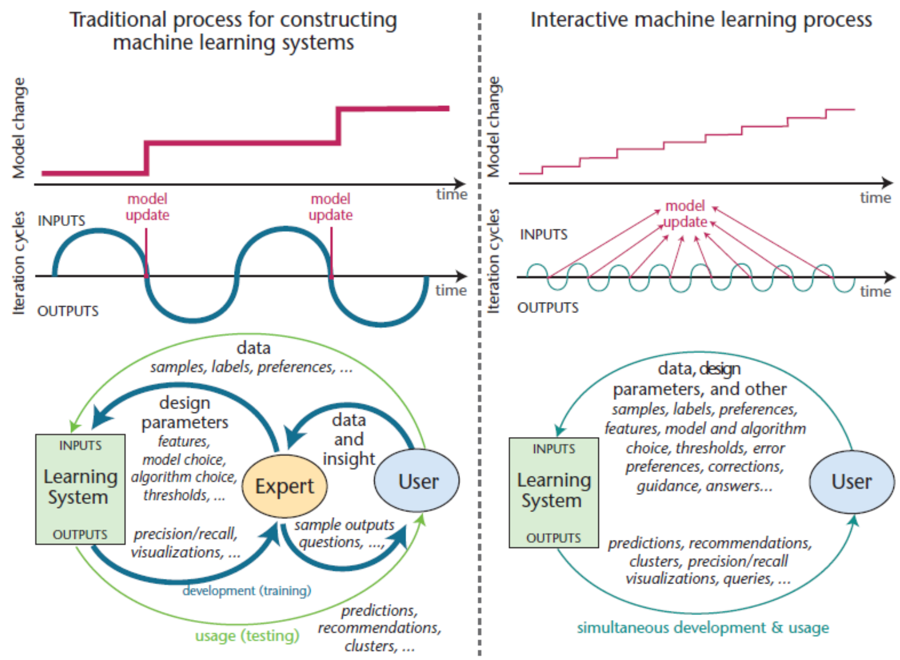


Figure 10. Comparison of Traditional aML to iML Processes. Source: [12].

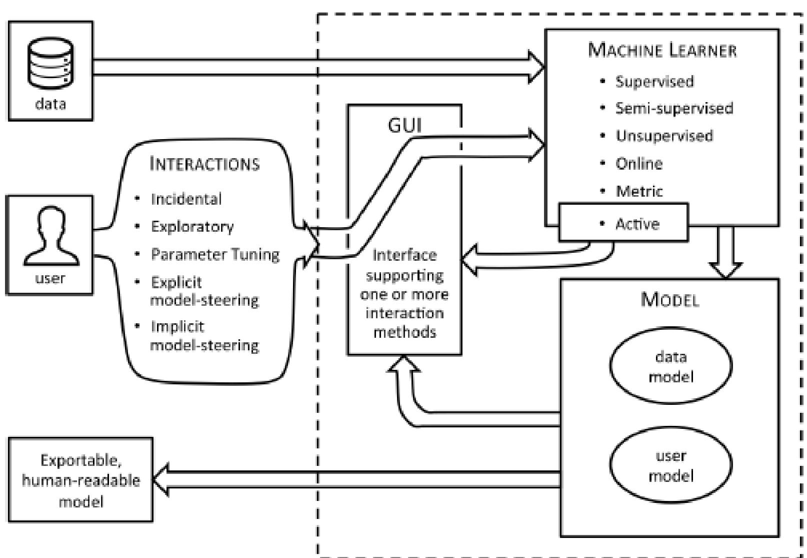


Figure 11. iML in a View Comparable to Figure 6. Source: [45].

To date, there are numerous research efforts into iML. These explorations include pixel and photo classifications to gesture recognition and Ant Colony Optimization, with motivations ranging from increasing the speed of the machine learning process to achieving transparency within the “black box” [46]–[49]. Elements of iML are explored within Section II.G.2 Interactive Machine Learning (iML). Another approach that utilizes an iterative and interactive process for education of AI agents is known as *interactive task learning (ITL)*. Laird et al. [50] show that ITL can work with ML techniques or be used as a standalone approach to educate an agent [50].

5. Interactive Task Learning

ITL is an approach to the education of the agent through an instructor to student relationship. The human is the instructor and the AI agent is the student. Within ITL, underlying concepts are explained and learned by the agent for the execution of a task. The agent learns and remembers concepts, tasks, goals, and definitions of objects [50]. This allows for the transferring of learned information from one problem set to another. “The primary goal of an interactive task learner is to learn a task from its interactions with an instructor and from its own experiences” [50]. This ability of the agent to learn through human interaction, via voice or physical control, is complemented by ITL’s design for broader problem sets compared to traditionally narrow problems of current AI research. As with the iML approach, the ITL uses a software development expert to create the learning operating systems of the agent and then removes the expert from the learning loop. The learning loop is then strictly dependent on the human (instructor) to agent (student) relationship [50].

6. Summary

Through the analysis of AI, it is evident that AI is the representation of an agent within a machine that can accomplish tasks normally requiring human intellect. It can recognize patterns, learn, infer information, and / or take actions. This agent can be represented digitally, as in a computer based system, or be internal to an autonomous physical system [23]. Continuing, all or some parts of a system can be automated. Automated elements are prescriptive and allow no room for flexibility [32]. In contrast, autonomous agents sense a broad range of inputs, understand the identified goal state, and can develop a plan to bridge the two [34]. The underlying agent for both automated and autonomous processes is developed in myriad of ways. One end of the spectrum is through a computer programmer's coding of conditional statements to produce the desired output. The opposite end of the spectrum is the use of an AI agent to create the associated logic through ML. The AI agent can be educated through multiple ML processes. An identified shortfall for aML processes is the byproduct of the "black-box" nature of the AI agent's logic to the end-user's understanding. Research is underway in areas to increase the interaction of the end-user into the AI agent's development process. Both iML and ITL show promise in tightening the relationship between the AI agent and end-user.

This sort of picture of AI agents and ML environments begins to create a concept that is analogous to the common phrase, "the right tool for the job." For spray painting cars on an assembly line, automated robotic arms effectively and efficiently accomplish the task [51]. For cleaning the floor in your house, an autonomous vacuum achieves the tasks. The robot understands that a clean floor is the goal and can accomplish this even when new disruptive objects are placed in the environment, e.g., a chair is moved from the last vacuuming [52]. Microsoft recently used ML techniques to aid in the classification of photos that captured elusive and rare snow leopards. They used hundreds of thousands of painstakingly human classified photos to train the system [53]. All aforementioned solutions work well in a deterministic environment and do not incorporate a human element. For agents that are intended to work with humans, the interactive approaches – interactive Machine Learning and Interactive Task Learning are viable options. To continue to explore how interactive approaches can be used, an understanding of manned-unmanned teaming is required.

F. MANNED-UNMANNED TEAMING (MUM-T)

1. Why MUM-T?

As AI and ML technology continues to improve, the goals for how machines— i.e., computers, robots, AI agents—perform in relationship to a human will continue to develop. According to Johnson et al. [54], with the technological advances, the idea of "teaming" will become a mainstay in man-unmanned vernacular [54]. Unmanned agents range in scale from teleoperated systems (remote controlled) to independent automatons (Roomba vacuums). Teleoperated systems require their inputs to be interpreted and decided upon by the human controller. The outputs are then triggered through some form of controller to the system to execute the prescribed action. The simplest, albeit most inefficient, form of teleoperation requires complete human attention. On the opposite end of the spectrum—a fully autonomous system—requires no human oversight. All inputs, decisions, and outputs are sensed, interpreted, decided, and actioned by the fully autonomous system. As detailed in Section C – Artificial Intelligence, Autonomy and Section D – Machine Learning, the primary shortfall of AI is its ability to handle novel situations. Published in 1978 by Sheridan and Verplank [55], Figure 12 shows the relationship between specified and novel situations to the amount of automation an agent can have [55].

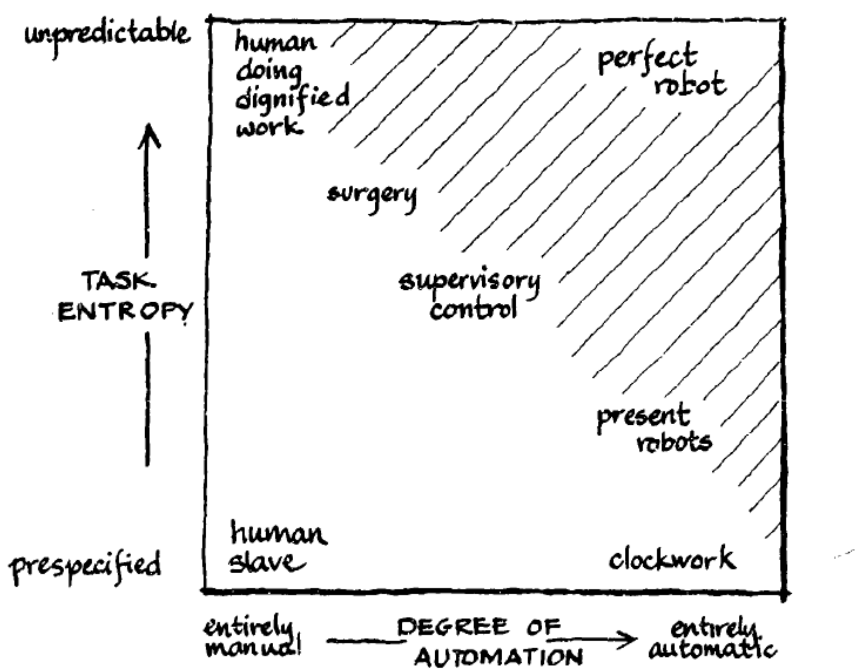


Figure 12. Task Entropy to Degree of Automation. Source: [55].

The figure creates a relationship between the types of tasks that are acceptable for an agent to perform dependent on the predictability of a task. The authors describe the degree of automation on a spectrum ranging from remote controlled to fully automated, and task entropy from completely known to fully unknown. In the bottom left, the human is in complete control of an agent executing pre-determined tasks, i.e., a mundane and repetitive task. Following this task to the right on the graph, shows the type of tasks that are ideal candidates for the agent to execute with minimal supervision. A modern-day example of this would be the Microsoft photo classification task. In the top left of the figure is the use of an agent or robot to conduct an unknown task in a dynamic environment. The top right is the agent completing that task without any human involvement, i.e., vacuuming a room. The transition between the white to shaded area was defined as the frontier by Verplank and Sheridan [55]. The relationship developed by [55] is also valid with autonomy. Since 1978, the frontier remains in the same region. AI agents are very good in known situations for predetermined tasks. This limitation, and thus the reduction of the frontier, can be overcome by the teaming of an AI agent with a human counterpart.

Verplank and Sheridan’s research focused on the use of unmanned robotic systems as an extension of a human controller in undersea exploration. Due to the difficulties of maintaining responsive and reliable communications with the underwater system, their explorations were to identify what tasks could be automated to the unmanned robot system. Their representation of manned unmanned teaming (MUM-T) shows the benefits of the teaming relationship. Though simplistic, and relating to undersea operations, the benefits of teaming (via “sharing” and “trading”) are easy to envision in other realms.

In Figure 13, the dotted horizontal line represents task accomplishment. The obvious goal of the relationships represented in the figure are to raise the task, “L,” above the line. In Verplank and Sheridan’s depiction, the box “C” represents a computer but can also represents the concept of a machine. Alone, the human, “H,” can accomplish the task, but within the “Sharing” realm the task is either accomplished to a greater degree, “Extend;” or alleviates the amount of work the human must do, “Relieve.” In the “Trading” area, the computer can “Back-up” the human’s work-load, but to a sub-optimal level if the human requires relief. The final option within “Trading” is where the computer “Replaces” the human; this does not accomplish the holistic task [55]. Within this thesis, the focus of MUM-T will be the "Extend" action for the overall task, and the "Replace" action for specific sub-tasks. This approach for MUM-T allows the team to do more. Additionally, the allocation of the right sub-tasks to the computer will free the human to execute more critical and cognitive tasks. The following section explores a human machine teaming model for the allocation of tasks and sub-tasks.

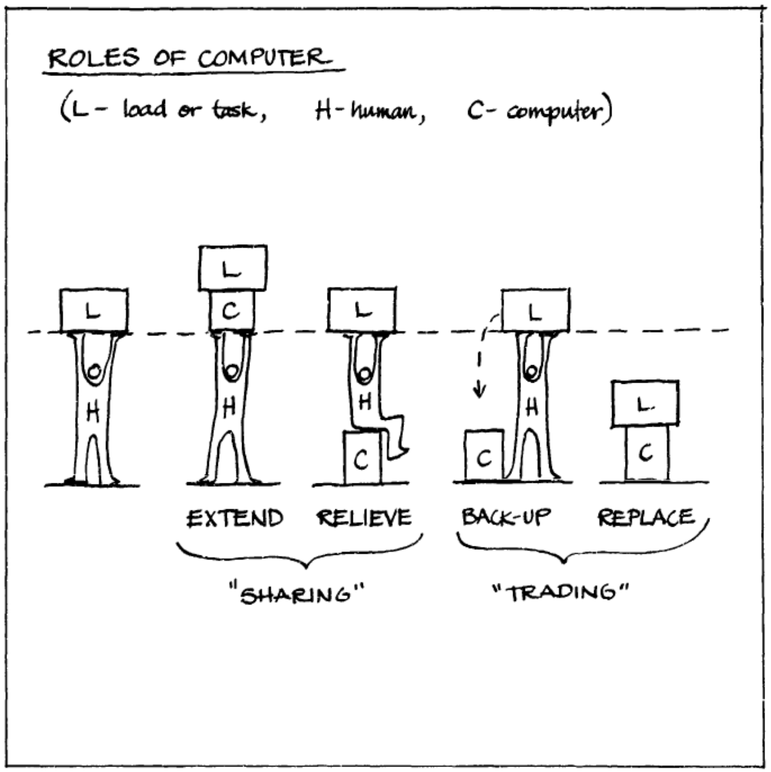


Figure 13. Benefits of MUM-T. Source: [55].

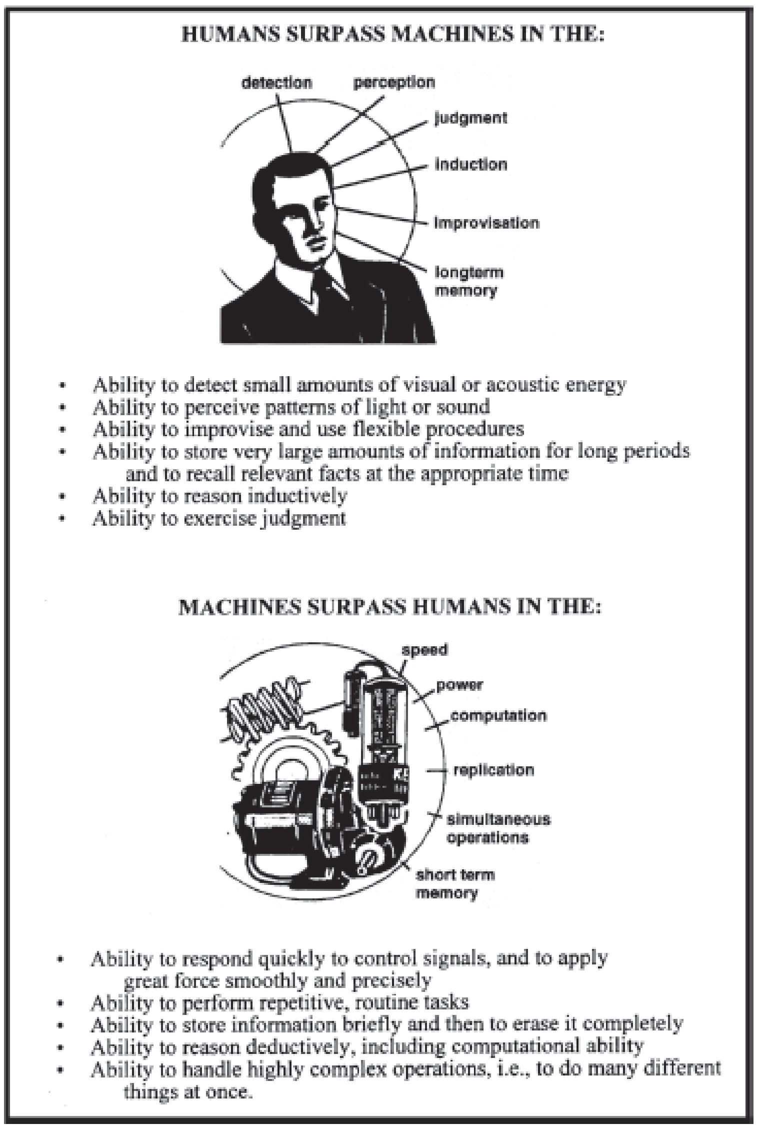
2. What is MUM-T?

The DoD's Unmanned Systems Integrated Roadmap [32] uses the United States Army's definition for MUM-T [56].

> Manned-unmanned Teaming [MUM-T] is the synchronized employment of soldiers, manned and unmanned air and ground vehicles, robotics, and sensors to achieve enhanced situational understanding, greater lethality, and

> improved survivability. The concept of MUM-T is to combine the inherent strengths of manned and unmanned platforms to produce synergy and overmatch with asymmetric advantages. [56]

This definition fits well into the current research on MUM-T. The most common model of MUM-T is the Fitts Model.



Bradshaw et al. state, "The Fitts HABA-MABA (humans-are-better-at/machines-are-better-at) approach. Reprinted with permission from Human Engineering for an Effective Air Navigation and Traffic Control System, 1951, by the National Academy of Sciences, courtesy of the National Academies Press, Washington, D.C." [57].

Figure 14. Fitts Model of MUM-T. Source: [57].

According to Bradshaw et al. [57], the Fitts Model, developed in 1951, is the delegation of sub-tasks between a human and machine to who can best accomplish that sub-task while aiding the team to better accomplish the overall task as shown in the "Extend" portion of Figure 13 [57]. The Fitts Model is also known as the "Humans Are Better At – Machines Are Better At" (HABA-MABA) model. Figure 14 compares the HABA-MABA abilities. It clearly breaks down the types of tasks that are good for humans and machines. The assessment of who does what better is still valid today.

The conglomeration of the Verplank et al. and Fitts Model fits well to how the USMC's *Marine Corps Doctrinal Publication 1 - Warfighting* [58], views the use of technology: "Equipment is useful only if it increases combat effectiveness" [58]. With regards to Figure 13, the dotted line is combat effectiveness. For achievement of the task above the combat effectiveness line, the teammate relationship between human and machine requires interdependence. Johnson et al. [54] utilize the Coactive Design process to develop the approach to design for interdependence. They state: "Interdependence describes the set of complementary relationships that two or more parties rely on to manage required (hard) or opportunistic (soft) dependencies in joint activity" [54]. The concept of interdependence is developed under three types of interactions. The interactions are symbiotic between the human and the machine to achieve true MUM-T. The three concepts are observability, predictability, and directability; [54] defines them as:

> Observability means making pertinent aspects of one's status, as well as one's knowledge of the team, task, and environment observable to others.
>
> Predictability means one's actions should be predictable enough that others can reasonably rely on them when considering their own actions.
>
> Directability means one's ability to direct the behavior of others and complementarily be directed by others. [54]

This again pairs nicely to the USMC's doctrine on cooperation and teamwork. *Warfighting* [58] builds from an idea presented by John Boyd's *Organic Design for Command and Control* about the idea of implicit communication within a command:

> Our philosophy of command must also exploit the human ability to communicate implicitly (Boyd). We believe that implicit communication— to communicate through mutual understanding, using a minimum of key,

> well-understood phrases or even anticipating each other's thoughts—is a faster, more effective way to communicate than through the use of detailed, explicit instructions. We develop this ability through familiarity and trust, which are based on a shared philosophy and shared experience. [58]

When synthesized, it creates a clear picture for the defining the goal for MUM-T to achieve the definition for MUM-T used by the DoD, [32]. Observability and Directability are encapsulated by the Marine Corps' use of implicit communication. A "mutual understanding" is the Observability of knowledge between both human and machine. The use of 'well-understood phrases' allows for the Directability of the elements of the team. Finally, the predictability is developed "through familiarity and trust." Trust is a critical element to the adoption and use of any system by a Marine – especially a teammate.

3. Trust in Automation

The DoD Roadmap for Unmanned Systems Integration [32] acknowledges trust as "complex and multi-dimensional" [32]. The same guiding document continues to develop trust as part of the life cycle of any system, and that there are multi-faceted roles of human trust in systems, ranging from end-users to policy makers. Additionally, the ability to maintain human authority within missional approval will aid in trust of MUM-T systems. Finally, "Without an adequate level of trust between operators/commanders and autonomous unmanned systems, to function properly with a high degree of consistency, these systems will not be used in any mission set" [32]. To create systems that will be used, an understanding of the elements of trust will create a bedrock for the life-cycle development of the autonomous system and their development and maintenance of trust with humans.

a. Elements of Trust

Seminal work by Lee and See [10] in human factors and trust in automation state that trust is the "attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability" [10]. Lee and See make a clear delineation between trust and reliance based on work from Ajzen and Fishbein. Lee and See produce, "trust is an attitude, and reliance is a behavior" [10]. They continue, "Trust guides—but does not completely determine—reliance" [10]. Though trust is a personal view, there are contextual elements that develop the user's approach to trust.

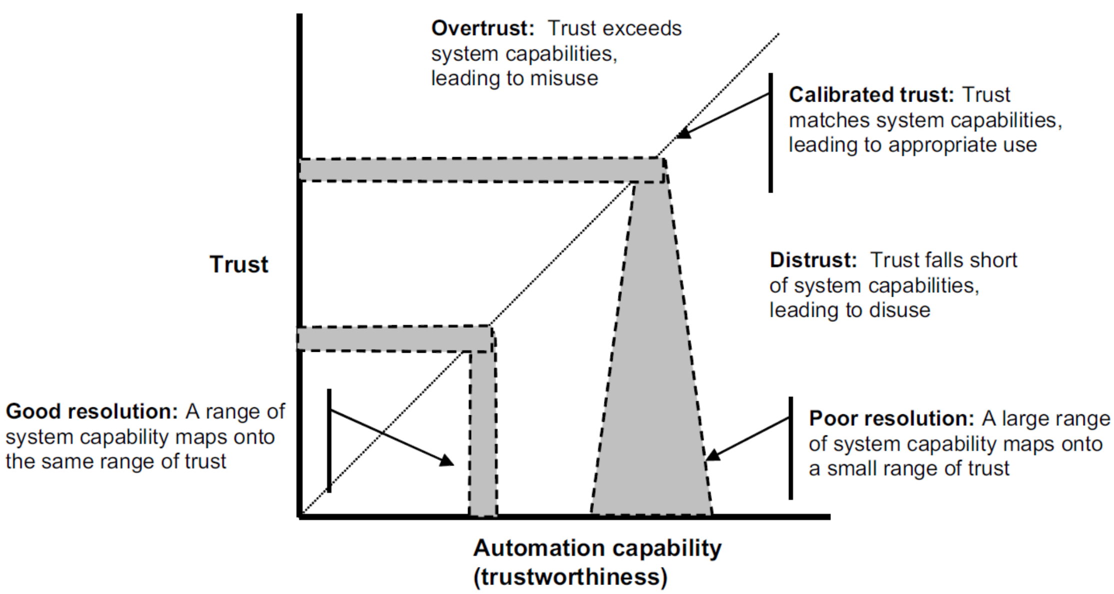
Lee and See continue, there are three additional contextual elements that shape and influence trust in autonomous systems: Individual, Organization, and Cultural Context. Individual context focuses on the user's experiences, self-confidence in task, and specific history that develops a level of trust. Organizational context involves the interactions between persons within the organization and how trustworthy the organization is. Cultural context is developed through the user's society's customs and expectations [10]. Continuing from the contextual elements that influence a user's trust, the user must also build trust through awareness of the autonomous system.

To have the appropriate trust in a system requires calibration, resolution, and specificity of the system. Lee and See build on concepts presented by Lee and Moray, 1994 and Muir, 1987, calibration refers to finding the center line of over-trust and under-trust, which [10] titles as distrust. Distrust will be used through the rest of this thesis. For resolution Lee and See utilize Cohen et al., 1999 to develop it as an understanding of the tasks and situations that fall within the systems capabilities. Finally, specificity is knowing which specific actions and components are to be trusted [10]. These elements of trust tie directly to the factors of the automated system through performance, process, and purpose. Performance is how well the automation operates. Process is how it operates. Purpose is understanding what the system was designed to do [10].

Tying these elements of trust together; calibration, resolution, and specificity of a system is the user's understanding of the autonomous systems capabilities for a specific task. Within the specific task; performance, process, and purpose are focused on "how" the autonomous system will perform that specific task. These elements of trust may be influenced by the user's own individual, organization, and culture context of the system and the associated tasks. These elements are brought together by the user's attitude towards the system. To achieve trust, familiarity with the system is required. The familiarity will build predictability, then dependability, and, finally, the attitude of faith in the system - trust. In 1987, Bonnie M. Muir [59] develops this idea as the calibration of trust.

b. Calibration and Accumulation of Trust

Muir's work extends a model of inter-human trust developed by Rempel, Holmes, and Zanna in their article, "Trust in Close Relationships." Muir takes the Rempel et al.'s trust model to "how a human's trust in a machine changes as a result of experience on a system" [59]. The resultant of the experience developed with a system is calibrated trust. A user who has appropriately calibrated their trust in an autonomous system will achieve the maximize value of the MUM-T as shown in "Extend" relationship of Figure 13. As mentioned, calibration is the centerline between over- and dis-trust. Over trust is the user's expectation that the system's range of capabilities, performance, and purpose are greater than they actually are. Distrust (under-trust) is the opposite. Byproducts of inappropriate calibration of trust are misuse – reliance on automation for incorrect tasks, and disuse – rejection of the capabilities of the automation [10]. Figure 15 shows the balance of trust and the automation's capabilities for the calibration of trust.



Lee and See state, "the relationship among calibration, resolution, and automation capability in defining appropriate trust in automation. Overtrust may lead to misuse and distrust may lead to disuse" [10].

Figure 15. Lee and See's Calibrated Trust. Source: [10].

In Cohen et al.'s [60] "Trust in Decision Aids: A Model and Its Training Implications," trust is developed as the product of interaction between the user and the system. This implies, that with every interaction, trust is evolving. To achieve appropriate calibration and resolution, familiarity with a system is required. Elements that influence the familiarity and the predictions of a system are many. They range from the user's experience with the system in a variety of tasks and scenarios, understanding of the system design and functionality, and reports by other concerning their experiences with the system [60]. The way to increase the user's exposure to these elements of familiarity and predictions is through experience with the system in training. Based on Marine Corps Doctrinal Publication 1-3 *Tactics*[61], the goal of Marine Corps training is to develop familiarity, trust, battle drills, and combat standing operating procedures (SOPs) [61]. Battle drills and SOPs develop expectations within a unit of who will do what specific actions during a task. This is very similar to the sort of relationship that is developed with an autonomous teammate.

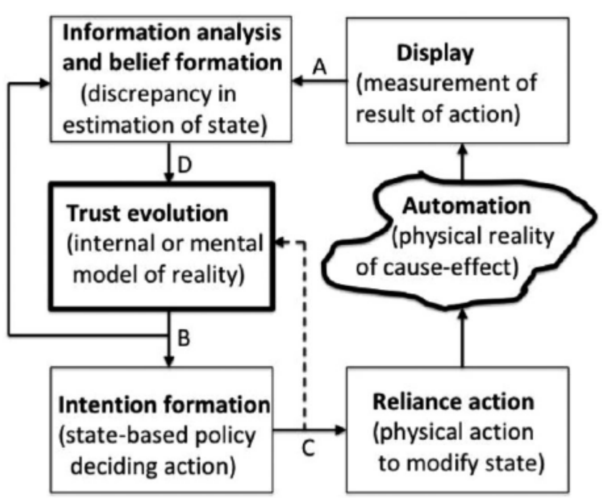
In review, the following elements are critical to the user in development of trust to with autonomous teammate:

- Resolution – Is this the right task for the autonomy?
- Calibration – Should the autonomy be used for this task?
- Process – How will the autonomy complete this task?

Additionally, the following factors of autonomous systems are essential for the user in their development of trust:

- Purpose – Was the autonomy made for this task?
- Performance – How well will the autonomy complete this task?
- Predictability – What will the autonomous actions be? [59]

These concepts are brought together in the form of a mental model. Sheridan [62] explains that the maintenance of the mental model takes the likeness to a Kalman control systems feedback loop and implies that trust is continuously calibrated. Sheridan modified the six major blocks of Lee and See's "Interaction of context, agent characteristics, and cognitive properties with the appropriateness of trust" model. The Sheridan updated version is shown in Figure 15. Sheridan has added the words in the parenthesis of each block, and the dotted line from state "C" to "Trust evolution." The words in parenthesis connect trust vocabulary to control system feedback vocabulary. The dotted line creates a connection on belief for when actions of the automation cannot be observed [62]. Lee and See's original model shows that appropriate trust is when state "A" and state "B" are equal. This holds true with Sheridan. Absolute calibration of trust is when the mental model of execution matches the actual displayed behaviors of autonomous systems. Though [10] and [62] present this model in from the user's perspective, the next step for MUM-T would be this same form of model from the unmanned teammates perspective, by replacing "Automation" with "Manned Activities." Two direct factor that are in the path of states A and B are the "state-based policy deciding action" and the "physical action to modify state." Of specific interest to this thesis, is the "state-based policy deciding action." Throughout this thesis, this factor was developed as the "agent" and at this point may or may not be explainable to the end-user.



Sheridan states, "Kalman estimation/control model of trust. Shown in parentheses are modifications of terms in bold taken from Lee and See's (2004) model" [62].

Figure 16. Sheridan's Control Model of Trust. Source: [62].

4. Summary

As AI continues to improve, so does the scope of tasks that an agent can complete. The tasks still being assigned to AI agents to complete are repetitive, mundane, and/or dangerous. This follows in line of the Fitts model – HABA-MABA. When in isolation, the accomplishment of the AI agent's task replaces the human. When multiple tasks are accomplished in a complementing nature by the human and AI agent – MUM-T – the results exceed then when both are accomplished in isolation. When the tasks complement each other, a major factor that influences the relationship is trust. The best way to gain and calibrate trust is through an intimate understanding of the system, what it was designed for, and how it functions. These elements come together for the user in the user's mental model of the system's behaviors. A way to develop the user's mental model of the MUM-T is through experience with the system which can take place in live or virtual environments. The team gains experience in an environment that allows for the elements of the interdependence model. The behaviors at state B must be observable. Observations at state B should match expectations at state A, thus predictability and calibrated trust. And finally, to achieve more together than alone, reference "Extend" from Figure 13, the teammates must be directable to achieve the appropriate tasks. A factor that has yet to be accounted for within Sheridan's Control Model of Trust is the "black-box" nature or explainability of the "state-based policy deciding action."

G. DEVELOPING TRUST WITHIN MUM-T

1. How Explainability and Trust link

The catalyst for the XAI program [42] from DARPA is captured by in the model created by the Florida Institute for Human and Machine Cognition in Figure 17. Their process incorporates the flow beginning with the user and ending with appropriate use. As shown, trust is a critical factor for the user and how the user employs the system. Working through Figure 17, the user receives an explanation from the XAI system that allows for the user to assess the explanation based on pre-established criteria. The criterion for assessment is shown in Table 3. As the user digests this explanation it updates the user's mental model of how the system should behave and re-calibrates trust for the system's actions. Once the system executes its task it allows the user to assess and improve the user's expectations for the tasks [42]. The green boxes in Figure 17 correspond to the descriptions provided in Table 3.

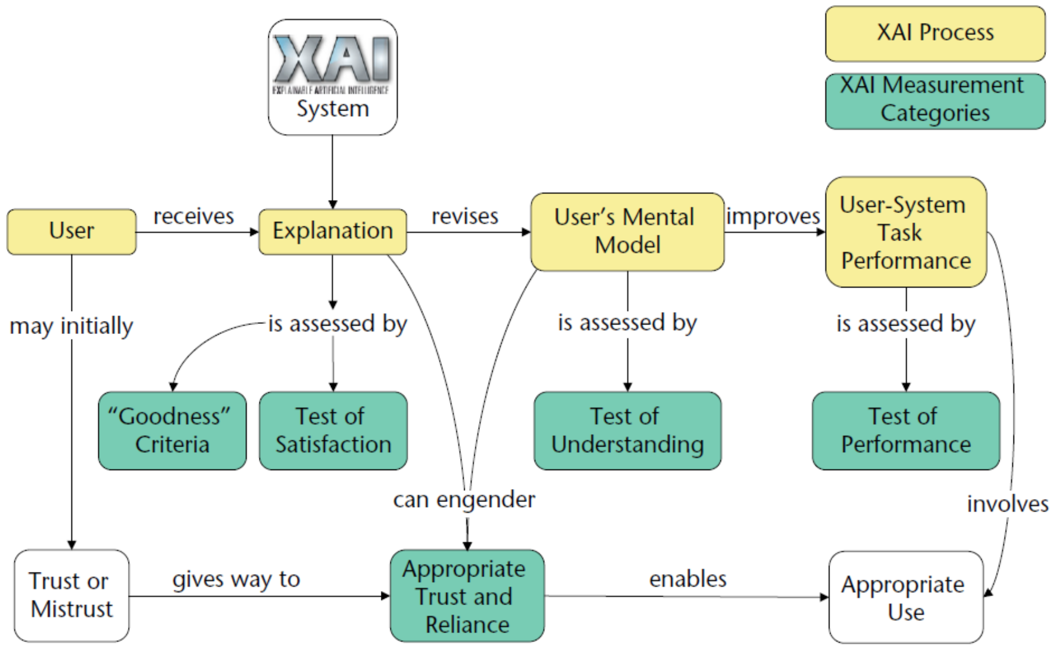


Figure 17. DARPA's XAI Explation Process. Source: [42].

Table 3. DARPA's XAI Explanation Measurement Categories. Source: [42].

Measure	Description
ML Model performance	
Various measures (on a per-challenge problem area basis)	Accuracy/performance of the ML model in its given domain (to understand whether performance improved or degraded relative to state-of-the-art nonexplainable baselines)
Explanation Effectiveness	
Explanation goodness	Features of explanations assessed against criteria for explanation goodness
Explanation satisfaction	User's subjective rating of explanation completeness, usefulness, accuracy, and satisfaction
Mental model understanding	User's understanding of the system and the ability to predict the system's decisions/behavior in new situations
User task performance	Success of the user performing the tasks for which the system is designed to support
Appropriate Trust and Reliance	User's ability to know when to, and when not to, trust the system's recommendations and decisions

The DARPA XAI research creates a baseline model. Research to build from the models produced by DARPA XAI, led to the 2019 International Joint Conference on AI (IJCAI). Within publication list, only two publication were focused solely on XAI, teaming, and trust.

In the first, Jianlong Zhou and Fang Chen [63] explore the interactions of trust with a predictive decision making AI system and the “human’s experiences with the system and domain knowledge” [63]. Motivations for Zhou and Chen’s research mirror that of this research - disuse and misuse of systems and the “black-box” nature of AI systems. Based on Lee and See’s definition of trust that describes uncertainty and performance as an element of the situation for trust, Zhou and Chen developed a tool that indicates the amount of uncertainty and performance that an AI model has in its own decision. The amount of uncertainty is measured by the difference between the real-world parameters for the AI agent’s decision making and the training model’s parameters used to create the AI. The performance is indicated by the expected outcome of the model. The uncertainty and performance indicator is a tool intended to trigger the right amount of trust by the human teammate. Utilizing a trial to trial experimental process, Zhou and Chen had success confirming that this approach increased the calibration of trust [63]. A secondary by-product that Zhou and Chen did not reference was the increased familiarity with the system as it iterated through simulations also increased the trust. The concept of repeating training cases in a simulated environment is valuable to this research.

In another article published by the IJCAI in 2019, Papenmeier et al. [64] measured the fidelity of the explained AI actions to trust. Papenmeier et al. define fidelity as: “how truthfully the explanation represents the underlying model” [64]. Through the use of Tweets possessing offensive language, the team varied the amount of fidelity of the explanation provided by the AI system to the user. The study involved manipulating the fidelity in three factors (low, medium, and high) of the reporting and accuracy in three factors (low, medium, and high) of the AI system across 40+ Tweets for each of 327 participants. Their objective results measuring trust indicated that fidelity does matter to the user. Low fidelity feedback had negative impacts to the system, but the model’s overall level of accuracy impacted trust the most. An important factor that does not involve fidelity or accuracy was the critical element that a “users’ awareness level influences their perception of trust” [64]. Though there is substantial work being completed on the explaining of AI actions, it may not be the ultimate tool in calibrating trust for a human with an AI agent teammate [64]. Connecting Papenmeier et al.’s research to Figure 17 and Table 3, the preponderance of research is conducted on the “Explanation goodness” and “Explanation satisfaction.” Elements of Table 3 that were previously explained prior to be introduced in the table are: “Mental model understanding” and “Appropriate Trust and Reliance.” The next portion will explore how a user can be involved with the development of the AI agent which will increase awareness and “Mental model understanding” and, in turn, trust.

2. Interactive Machine Learning (iML) Research

In an aptly named review, “Power to the People: The Role of Humans in Interactive Machine Learning” focused on iML techniques, Amershi et al. [12] select specific research in iML to demonstrate the importance of understanding how to interact with the end-user. Utilizing a ML project completed in 2006 by Caruana et al. as a case-study, Amershi et al. present the concept of enabling users to explore the AI Agent’s model space with less supervision from ML experts. The case shows that users were empowered to create and employ ML for their own desires and purposes. Amershi et al.’s research reveals the three following points:

> Rapid, focused, and incremental learning cycles result in a tight coupling between the user and the system, where the two influence one another. As a result it is difficult to decouple their influence on the resulting model and study such systems in isolation.
>
> Explicitly studying user interaction can challenge assumptions of traditional learning systems about users and better inform the design of interactive learning systems.
>
> The ways in which end users interact with learning systems can be expanded to ways in which practitioners do (for example, tuning parameters or defining new constraints); however, novel interaction techniques should be carefully evaluated with potential end users. [12]

After Amershi et al. reviewed iML work completed by Fails and Olsen's on photo classification and Fiebrink et al.'s work with gesture based musical instruments; Amershi et al. show that the iML developed AI agents have an intrinsic link to the user that trained the AI agent. Additionally, it is shown that the user learned about the processes and procedures of the iML system for what the AI agent can comprehend [12]. This concept directly impacts the bi-directional MUM-T concepts of Observability, Predictability, and Directability, and the "User's Mental Model" shown in Figure 17.

Two other documents within Amershi et al.'s research concluded that "People want to demonstrate how learners [AI Agents] should behave" [12]. This point was based on research by Thomaz and Breazel [65] who created an iML environment for teaching an AI agent how to bake a cake. [65]'s research revealed that the instructors of the AI agents were able to develop a mental model of the AI agent's capabilities and behaviors, and the instructors took a proactive approach to demonstrating to the AI agents how to behave. Thomaz and Breazel conducted multiple iterations of the experiment with modifications to instructor inputs, the performance of the AI agent's learning improved as the instructor was able to demonstrate more behaviors to the AI agent [65].

The other research supporting the concept of instructors demonstrating to AI agents was conducted by Kaochar et al.[66]. This group explored different ways to interact with the AI agent using a simulation for an Unmanned Aerial Vehicles (UAV). Through a "Wizard of Oz" (WOZ; when a human takes on the responsibilities of what the user perceives as an AI agent) protocol, users were able to teach an electronic "AI agent student," actually a human, through a user interface that allowed both voice and control inputs. Within the experiment, users had an interface that allowed instructions to the "AI agent student," a timeline showing all previous instructions to the "AI agent student," and a map depicting the movements and behaviors of the "AI agent student" in the UAV. Within the instruction interface, there were four types of teaching styles allowable: 1. Teaching by demonstration, 2. Teaching concepts by examples, 3. Teaching by reinforcement, 4. Testing [66]. Kaochar et al. conclude that human teachers used a combination of all styles to provide instruction to the AI agent student [66].

The concept of 'users want to demonstrate how learners behave' is the catalyst for how the user will interface with the AI agent in the current thesis research. Though both [65] and [66] focus on human-agent interactions, they do not transfer the AI agent to a live execution. While [65] explores the concept of mental models, these researches do not explore how trust is developed by the iML.

a. iML and Trust

The closest aligned research on iML for trust in MUM-T was conducted by Robert Gutzwiller and John Reeder [44]. They used a purely virtual environment for their research with the aim to have a user calibrate their trust in a system by training the system's agent as to allow for an understanding of the autonomous system's abilities and behaviors. This aligns to a user's understanding of the purpose, performance, and predictability of an autonomous system's abilities and behaviors thus allowing for calibrated trust by the user as outlined by [10]. Gutzwiller and Reeder chose to move away from the more transparent forms of AI agents to use a neuroevolutionary computation method for maximum growth of the AI agent. Neuroevolutionary is a type of neural network that evolves with training and falls within the "hard to explain" category but allows for the optimum use of the AI agent. Their hypothesis was: "That iML will develop behaviors that adhere more closely to the user goals and expectations" [44]. Gutzwiller and Reeder had three research questions:

1. Does the incorporation of humans in deriving ML algorithms, through IML, lead to more human trust in the plans that are generated?

2. Do participants, who helped generate plans, recognize, and be able to differentiate between IML and black box plans (which used neuroevolution, but no human involvement)?

3. Does the amount of neuroevolution that occurs, represented as steps, affect either trust or plan recognition [44]?

Their research was a three phased experiment consisting of training, comparing, and labeling for the development and employment of a system tasked to conduct a search. Initially, the autonomous systems were trained by the user through the user defined goal states and guidance in a virtual environment to create a search plan. This plan was classified as an iML search plan. During the comparison phase, an iML and black box system search plans were shown to the user. The user then selected which search plan the user best believed would cover the required area. Subsequently, the user chose the trust score for the search plan from 1 to 100, with 1 for no trust and 100 for complete trust. The final phase, labeling, began with the showing of a plan in action. During the labeling phase, the participant decided if the plan was either iML or black box. The results are interesting: "iML plans were chosen more, but trusted less" [44]. Aligned to the research questions were: 1. The user trusted the IML developed plans less. 2. Users were able to accurately discern the difference and appropriately label the iML plan or aML plan. 3. There was no difference in user's awareness of the amount of neuroevolutionary steps. In their discussion, Gutzwiller and Reeder point out that a user's behaviors were quickly adopted by the AI agent in the iML learning phase. Based on their experimental design, the user did not score their trust in their own iML AI agent, but another participant's. This adoption of a user's behavior may be the reason why a different user trusted it less than an aML AI agent, but were easily able to identify the iML AI agent. The research from in this thesis will align the same user with their own perceived iML AI agent.

b. DARPA SQUAD-X

Additional programs that are exploring MUM-T for the DoD are led by DARPA. Two complementary programs focused on the MUM-T at the lowest tactical levels are the Squad X Experimentation and Squad X Core Technologies. According to their program information webpage [67], the goal of these programs are to "design, develop, and validate autonomous system prototypes and equip them with novel sensing tools and off-the-shelf technologies" [67]. Technologies and autonomous systems that the Squad X programs are exploring are to help infantry squads increase their situational awareness, battle space, and influence. Of the four technological development areas, the "Squad Autonomy" effort is closely aligned with this work. They aim to increase intra-squad real-time awareness between all teammates and explore "robot collaboration between humans and unmanned systems" [67].

Through the multiple experiments performed by the Squad X program, the team has developed ground unmanned systems that possess varying levels of autonomy. According to a final report on fielding testing [68], the unmanned systems were tested as teammates for the squad and used to provide security and overwatch during military operations in urbanized terrain (MOUT) operations. It is unclear on how the autonomy was developed for the autonomous ground robots, but the approach to the autonomous algorithms were modified from aML to a human in the loop process during an inter-experiment technology development period. To bring the human into the loop, a realistic simulation environment was developed. The simulation allowed for the effective tuning of the unmanned system by the squad leader and evaluation of the virtual rehearsal of complex mission scenarios. The simulation aimed to involve the squad leader into the iteration process of the autonomous agent's development. Within the simulation, the squad leader was able to adjust opposing and friendly force actions and record autonomous behaviors. The autonomous agents were then able to be tested in multiple simulated terrain environments [68].

Motivations for this human in the loop simulation process are unclear, but it appears that the results are promising due to the effort applied by the Squad X program. There is no associated data for levels of trust or cognitive load. The process to incorporate the squad leader into the developmental process of the autonomous agent's behavior is the aim of this research. DARPA Squad-X and research by Gutzwiller and Reeder are the closest research to this thesis. Their commonality of using virtual environments to develop AI agent behaviors, and Gutzwiller and Reeder's analysis of trust following AI agent behavior development drive directly towards the experimental design for this thesis.

H. SUMMARY

Teaching and developing AI agents within a simulated environment by the end-user indicate there is the potential for better trust in the AI agent by the end-user when placed as a teammate within a MUM-T. Throughout the past chapter, it is shown that virtual environments serve as an area for the development of experiences for Marines, robots, and AI agents. Through an analysis of automation, autonomy, and AI; autonomous systems with AI agents can deliver the decision-making power to learn and adapt to changing environments. Computing speeds and different types of ML algorithms serve as the catalyst for the increased capabilities of AI agents and surge of DoD concepts to maximize the use of unmanned assets. Some unmanned assets will be partnered as teammates to Infantry Marines as autonomous unmanned ground vehicles controlled by an AI agent. Through the different types of ML algorithms, varying levels of capabilities emerge for the AI agent. As learning capabilities and performance of the AI agents increase, so does the in-explicable nature of their behaviors and reasoning. The in-explicable nature is shown to degrade the amount of trust that a user can place into the AI agent and thus decreases the efficiency of the MUM-T. Research has revealed that a way to protect against this vulnerability of AI agent behaviors is through the approach of iML. Through the user's involvement as the critic within the ML phases, either as the reinforcer or supervisor, it is expected that the user will have a better mental model of the agent's behaviors for execution. The increased resolution of the user's mental model will allow for a better calibration of trust. This in turn will increase the efficiency of the MUM-T.

III. METHOD

A. DESIGN

The design of the experiment is a two-group comparison design, with iML and aML manipulated between groups. Of interest is the participant's trust between groups, which was measured in the participant's (a) robot choice (teleoperated robot or autonomous mode), (b) performance, and (c) robot monitoring via eye tracking.

The two hypotheses tested are:

- H1: There will be a greater proportion of Marines who will choose to use the "autonomous" robot over "teleoperated" in iML vs aML condition. ($p_{iML} - p_{aML} > 0$).

- H2: There will be more indicators of trust for the iML than the aML conditions. ($\mu_{iML} - \mu_{aML} > 0$).

B. PARTICIPANTS AND LOCATION

Utilizing previous literature, [44], and the Cohen's d approach; a power analysis was conducted to determine the appropriate sample size with an effect size of 0.72, alpha = 0.05, and power = 0.80. The analysis resulted in a total of 50 participants. Due to a cold-front and snowstorm in the North Carolina region during the experimentation week of 17-21 February of 2020, only 40 of the targeted 50 participants were able to participate. Group A is associated with iML and Group B is the aML factor.

The target population of employment of future MUM-T systems are Infantry Marines at the squad or lower level. To meet this demographic, participants were students in the Advanced Infantry Training Battalion – East's (AITB-E) Advanced Infantry Marine Course curriculum at Camp Lejeune, NC. Out of the 40 Marines that participated, 37 were in their final week of training in the of the curriculum, and the 3 other participants were Infantry Marines who volunteered from the AITB-E command. All participants were Infantry Marines with the rank of Lance Corporal to Sergeant, thus meeting the target population. The population was all male; there were no females enrolled in the Advanced Infantry Marine Course during the experimentation week.

The live execution environment was at Camp Lejeune, NC's "Enhanced-MOUT" Training Area (E-MOUT) as shown in Figure 18. The "Training" and "Live" portions of the experiment occurred in Building 31 of E-MOUT. Building 30 would be the objective building for the live portion.

Building 31 is represented by the blue star and Building 30 was the objective building represented by the red star.

Figure 18. Overview Map of Building 30 and 31 of E-MOUT.

C. MATERIALS

1. Participant Workstation

The following gear set was used to create the participant's workstation:

- Two Alienware M51 Laptop Computers
- One GoPro Video Camera
- Tobii Pro Glasses

- Portable Computer Screen
- Microsoft X-Box Controller

Figure 19 shows the participants' work-station in Building 31. The laptop on the left was used for the attention enumeration task, while the laptop on the right was used for the serious gaming. In the figure, it is currently showing the set-up for live execution with the small unmanned ground vehicle (SUGV) robot screen. The tablet in the far right of the figure is connected to a SUGV radio to relay the picture onto the screen on the right laptop. The large tan cases are the carrying cases for the SUGV systems.

Figure 19. Overview of the Experiment Room in Building 31 of E-MOUT.

2. Robots

Two Small Unmanned Ground Vehicles (SUGV) Systems, data sheet shown in Figure 20, were used for the robot within the experiment. The robots were man-packable and electric powered by BB-2590 military issued batteries. The user interface for the SUGV is shown in the top right picture of Figure 20. The user controlled the system through touching the associated "tablet." The system is entirely remote control with no autonomy. There were automated movements to place the robot into "drive," "stow," or "look-over" mode. The "peaky mode" verbiage was used in replacement of "look-over" with the participants. The two systems were temporarily loaned from 2d Explosive Ordinance Disposal Company, 2d Marine Logistics Group from Camp Lejeune, NC.

DETAILS

Accessories
Flatbed Backpack - Accommodates SUGV, controller, batteries and accessories.
FLIR LWIR Thermal Camera- the thermal image transmits directly to the robot's tablet controller.
Adaptive Specialty Probe Tool Kit for PackBot and SUGV - four specialty tools for cutting, raking, scraping and probing IEDs and other hazards.
Disruptors and the Firing Control System - accommodates recoilless disruptors. Uses a third-party firing circuit.

Product Specifications	
Weight - Mobility platform, manipulator and 2 BB-2557 batteries	30.6 lb (13.8 kg)
Runtime	Up to 6 hours
Mobility - Speed	Up to 6.2 mph (10 km/h)
Mobility - Agility	Zero radius turn
Mobility - Slopes	40° (ascend, descend) 30° Lateral
Mobility - Vertical Obstacles	12" (30.5 cm)
Mobility - Stair Climbing	38° [rise 8" (20.3 cm), run 10" (25.4 cm)]
Manipulator Lift	>22 lb (10 kg) close-in >12 lb (5.4 kg) at max extension [(24" (61 cm)]
Awareness	Four (4) cameras
Compatible	Connects to the Wave Relay® MANET, to form a robust network in which robots, operators, and observers seamlessly operate together.
Expansion	Multiple payload ports, multiple accessories, sensors and disruptors supported
Controller	uPoint® Multi-Robot Control System
Export Regulations	EAR

Figure 20. Data Sheet for SUGV. Source: [69].

3. Visual Attention Task

The visual attention task was a sub-program of the software titled *Presentation* by Neuro Behavioral Systems. The parameters for the attention enumeration task were five seconds for observation of the blocks and five seconds to enter the correct response. The space bar and enter button were used to trigger the next sequence. Figure 21 shows the full instructions provided to the participant. The attention enumeration task baseline began with a six-question tutorial under the supervision of a researcher. During the tutorial and testing period, the number of blocks on the screen would range from three to nine. A total of 10 questions were asked for each number. Figure 22 shows examples of what the test screen looked like during execution. The order of questions was randomly assigned by the program for each participant.

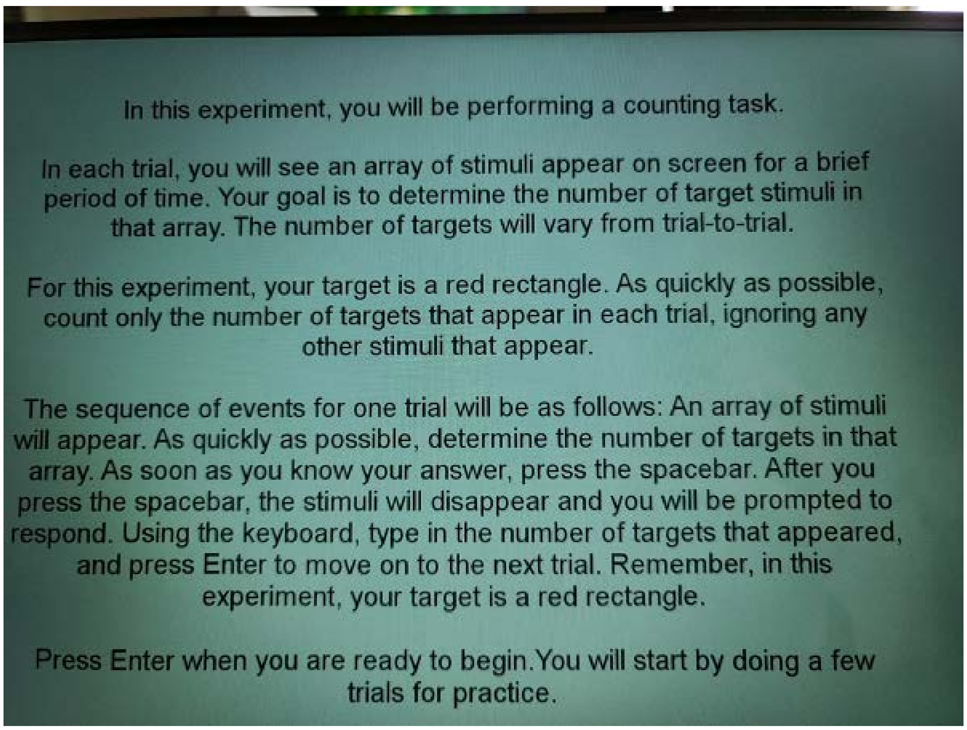
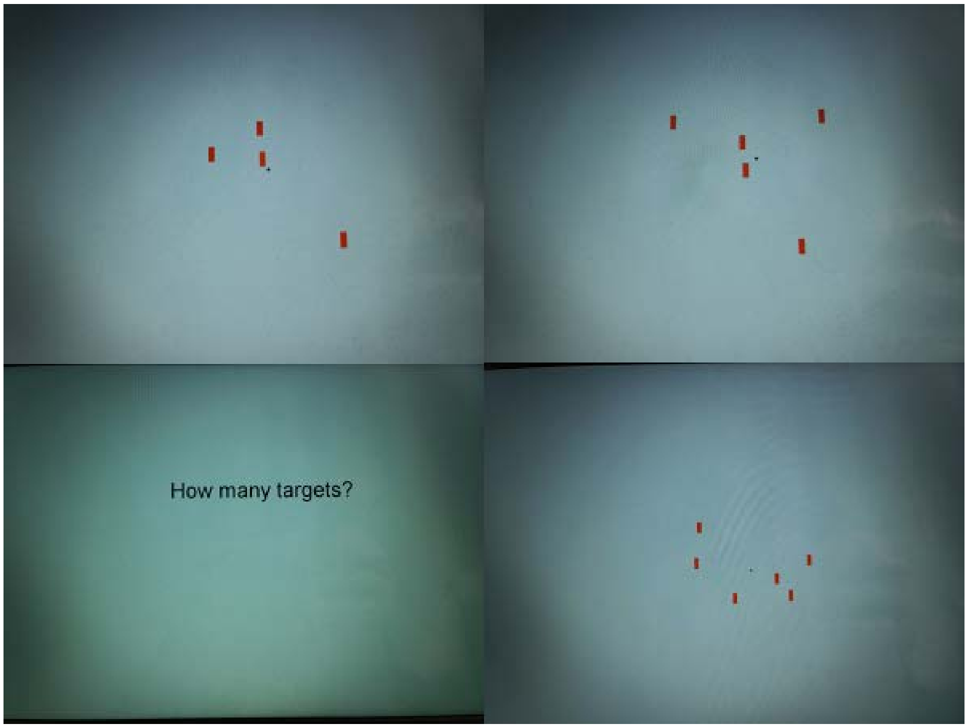


Figure 21. Instructions for Attention Enumeration Baseline Task.



Four different screen captures of the execution of the attention enumeration task are shown. The bottom left is when the participant would enter the number of red blocks counted via the keyboard.

Figure 22. Screenshots of the Attention Enumeration Baseline Task.

4. Virtual Training Environment

A serious game was created by the Modeling Virtual Environments and Simulations (MOVES) Institute, Futures Technology Department to be used as a training tool for learning the capabilities and limitations of the SUGV. The serious game had a tutorial to teach the participant how to use the keyboard or gamepad. A gamepad map, as show in Figure 23, was provided to the participant for use during the game. The tutorial showed the different speeds, positions, and camera views available to the SUGV. The SUGV modeling for the game was as accurate as possible based on developer testing at the Naval Postgraduate School (NPS) and data from the FLIR SUGV Data Sheet, Figure 20. Screenshots of the different steps within the Tutorial Phase are shown in Figure 24.

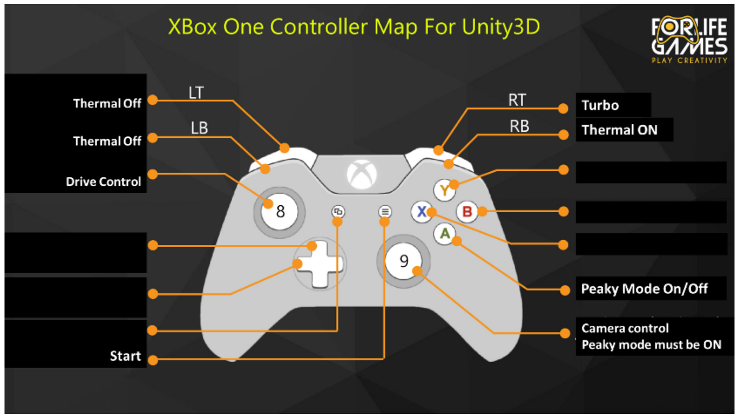


Figure 23. Controller Mapping. Adapted from [70].

Figure 24. Tutorial Screen Shots.

Once the tutorial was complete, the concept for the next five levels was the same for each group, but verbiage and elements on the screen were different. The five levels were developed to mimic basic MOUT training an entry-level Marine would go through. The levels and purpose are outlined in Table 4. The number of task iterations was driven by the requirement to have a realistic expectation that the repetitions were training the robot for Group A (iML). No explanation for the number of iterations was provided to Group B (aML).

Table 4. Familiarization Training Curriculum

Level	Purpose	Number of Iterations
Lesson 1	Basic Hallway Movements	16
Lesson 2	Room Search Methods	1
Lesson 3	Room Entering	5
Lesson 4	Anomaly Object Interactions	10
Lesson 5	Courtyard Movements	6

Group A (iML) was led to believe that the gaming situation was an iML environment. This was shown by the neural network diagram in the top left that updated after each iteration of the task. Verbiage for the Group A (iML) version of the game focused on the participant "teaching" the robot on how to perform those tasks, while the Group B (aML) version of the game had the participant "learning" on how to perform those tasks. The serious game for both groups was intended to have the same effects as normal training in virtual environments achieves as referenced in Section II.B.1. Simulations in the USMC. There were no machine learning indicators for any of the actions for Group B (aML). A comparison of Figure 25 and Figure 26 shows how that information was presented to the participant.

Verbiage in the top right of each screen shot is focused on the participant teaching the SUGV avatar. Top Left: Completion of Tutorial Screen. Top Right: Lesson 1. Middle Left: Lesson 2. Middle Right: Lesson 3. Bottom Left: Lesson 4. Bottom Right: Lesson 5.

Figure 25. Screenshots during Group A Version of the Game.

Verbiage in the top right of each screen shot is focused on the participant learning the capabilities and limitations of the SUGV. Top Left: Completion of Tutorial Screen. Top Right: Lesson 1. Middle Left: Lesson 2. Middle Right: Lesson 3. Bottom Left: Lesson 4. Bottom Right: Lesson 5.

Figure 26. Screenshots during Group B Version of the Game.

5. Trust Questionnaire

At the conclusion of the live execution, the right laptop would be connected to the internet and so the participant could take a pre-programmed online survey via Qualtrics.com. The survey that followed is the widely used Trust in Automated Systems Survey by Jian et al. [71]. The 12-question survey is shown in its original form in Figure 27. This survey was randomized for the participants to prevent biasing [72]. Questions 1-5 are negatively biased questions so the score for each of these questions were subtracted from 7 to provide a common reference across the survey. A lower score from this survey indicates less trust in the automated system. The questions appeared sequentially and had to be answered before continuing to the next question. Figure 29 shows the format for how each question would be answered. The survey automatically closed once all questions were complete.

Checklist for Trust between People and Automation

Below is a list of statement for evaluating trust between people and automation. There are several scales for you to rate intensity of your feeling of trust, or your impression of the system while operating a machine. Please mark an "x" on each line at the point which best describes your feeling or your impression.

(Note: not at all=1; extremely=7)

1 The system is deceptive

1 2 3 4 5 6 7

2 The system behaves in an underhanded manner

1 2 3 4 5 6 7

3 I am suspicious of the system's intent, action, or outputs

1 2 3 4 5 6 7

4 I am wary of the system

1 2 3 4 5 6 7

5 The system's actions will have a harmful or injurious outcome

1 2 3 4 5 6 7

6 I am confident in the system

1 2 3 4 5 6 7

7 The system provides security

1 2 3 4 5 6 7

8 The system has integrity

1 2 3 4 5 6 7

9 The system is dependable

1 2 3 4 5 6 7

10 The system is reliable

1 2 3 4 5 6 7

11 I can trust the system

1 2 3 4 5 6 7

12 I am familiar with the system

1 2 3 4 5 6 7

Figure 27. Jian Trust in Automation Survey. Source: [71].

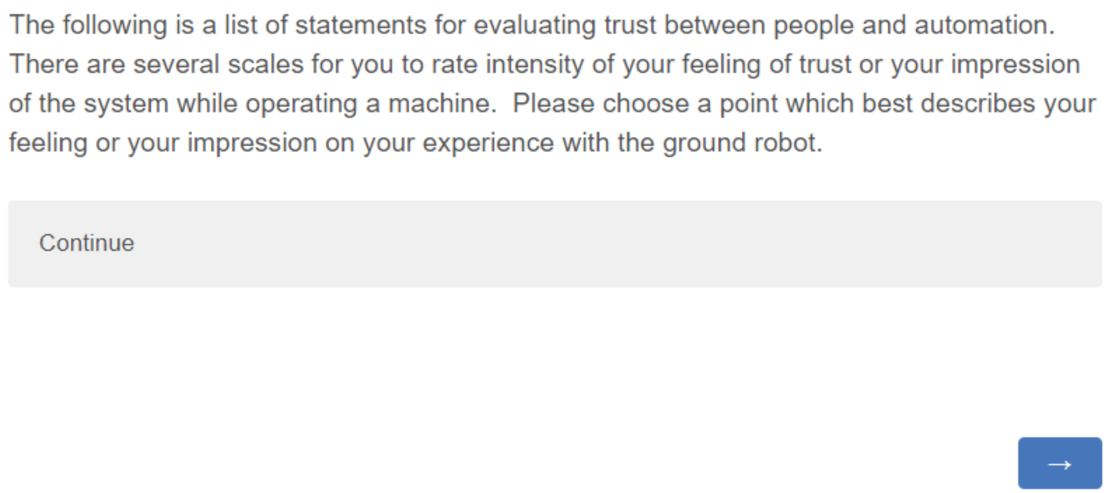


Figure 28. Instructions for Survey.

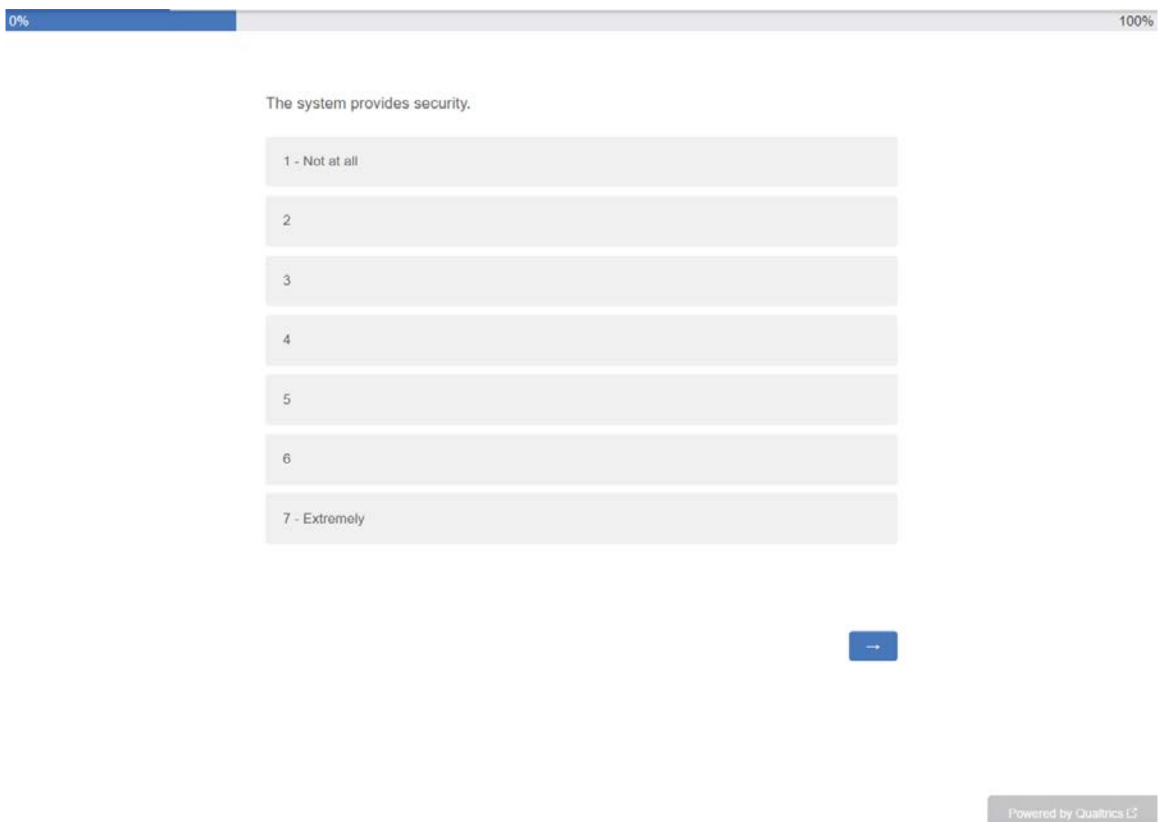


Figure 29. Example Survey Question.

D. PROCEDURE

The expected number of 50 participants was divided into two equal groups and their participant numbers were randomly assigned to either Group A (iML) or Group B (aML). They were transported to the experimentation area, Building 31 at E-MOUT, by an AITB-E HMMWV in groups of four to five from where the unit was training. Upon arrival, they were given the initial consent briefing and form. As a participant entered the workstation building, they would bring their signed and completed initial consent form with them. The following sections outline the process for the experimentation.

1. Introduction

Prior to the introduction being provided, the researcher would begin a new recording session on the GoPro video camera. The researcher would welcome the participant with the following introduction: "Thank you for volunteering to help with the experiment. The first task I'm going to ask you to execute is an attention enumeration task. This task represents the tasks that a squad leader must do during MOUT operations. It represents tasks like assigning sectors of fire, cross-boundary coordination, call for fire, and various other tasks that you would have to do. There is no easy way to baseline each Marine in those tasks; the next best option is the attention enumeration task."

2. Attention Enumeration Baseline Task

The participant would complete the initial attention enumeration task. During the tutorial portion of the initial task, a researcher would remain in the room to assist the participant in the procedures of the test. During the baseline testing portion, the researcher would leave the room and the participant would complete 70 individual tasks.

3. Situational Briefing

Upon completion of the attention task, the participant transitioned to the serious game. If the participant was in Group A (iML), the participant was told the following information:

"The video game you are about to play will inform you on the capabilities and limitations of the robot for MOUT operations. *The robot is also learning how you control it and how you perform each task as the robot in the game*. Once we complete the video game training you will have a live execution task of 'Clear the adjacent courtyard & building.'" The researcher would reference Figure 18 for the participant's situational awareness. "To assist you in this task, you will be able to use a real robot in either 'remote control' or '*user-trained autonomous*' mode. In conjunction with that task you will have to complete another attention task. The ability to send Marines into the next building is at the end of the next attention task. Again, the attention task is representing you, as the squad leader, 'setting conditions' for your squad to advance."

If the participant was in Group B (aML), the first italicized sentence directly above would be removed, and the second italicized portion would be replaced with "autonomous mode." The following description of autonomous mode was provided: "*The autonomous mode is currently the best in the Silicon Valley industry."*

4. Virtual Training and iML

After completing the briefing of the future live execution task, the participant would begin playing the serious game. Once the game was completed, Group A (iML) participants were briefed again: "Now that you've gained experience with the capabilities and limitations of the robot and *its learned from your actions in the video game,* for the next task would you like to use the robot in either complete remote control or *complete user-trained autonomous* mode?" Group B (aML) participants were briefed: "Now that you've gained experience with the capabilities and limitations of the robot in the video game, for the next task would you like to use the robot in either complete remote control or *complete autonomous mode*?" For each participant the decision was recorded. If the participant chose to use the robot in remote control mode, two researchers attempted to connect the gamepad controller to the SUGV, but it would not connect. This was a planned deception within the experiment. The participant was informed, "We're having issues with the remote control. The participant before you accidently dropped it. For the interest of time, can we just use it in autonomous [or user trained autonomous for Group A] mode?"

Since the SUGVs are strictly remote control from the manufacturer. A man behind the curtain, in a Wizard of OZ (WOZ) format [73], was controlling the robots for both Group A (iML) and Group B (aML). For Group A (iML), the WOZ was in the room observing the behaviors desired by the user. The participants were told, “This gentleman created the serious game – he’ll be in here in case you have any questions or concerns on the game.” Decision points were recorded by the WOZ. The behaviors and decision points are listed in Table 5.

Table 5. Behavior Decision Points for the WOZ

Decision Point	Behavior Option 1	Behavior Option 2
Courtyard Movement Speed?	Fast	Slow
Box Interrogation?	Yes	No
Peaky Mode for Room Entering?	Yes	No
Search Pattern?	Perimeter	Straight to Door

For the participants within Group A (iML), a batch file was executed to “compile and export” the data from the serious gaming computer for the upload to the robot with the participant’s behavior. A researcher moved to the SUGV and acted as if he were uploading the behavior files. Again, this was a point of deception to the participant as the serious game was not programmed as such.

5. Live Execution

Once the participant was prepared to not use the SUGV in remote control mode, Group A (iML) participants were told: “Currently, the robot is programmed to leave and return to the spot outside of our current building. *Your training of the robot in the game* will determine how the robot will behave in the courtyard and objective building.” Group B (aML) was told, “Currently, the robot is programmed to leave and return to the spot outside of our current building. *The coding from the engineer* will determine how the robot will behave in the courtyard and objective building." As this was being explained to the participant, a researcher showed the robot's planned movement. This is shown by the dotted red line in Figure 30. For both groups: "Again, the theory is to use the robot as a reconnaissance element before sending a team of Marines into the objective building. The completion of the attention task allows for the Marines to begin movement from the building directly to our east [researcher would point to the building] to the objective building. You can execute the attention task either simultaneously or sequentially as the robot performs the reconnaissance. If the robot detects an anomaly it will make an alarm sound."

Figure 30. Planned SUGV Movements.

After this briefing, the participant placed on the Tobii Pro Eye tracking glasses. The glasses were calibrated to each participant with the provided calibration card within the Tobii Pro Eye Tracking System. Following the calibration, the attention enumeration task 2 was transitioned to the start screen. The test was the same as the baseline test, minus the tutorial at the beginning. Additionally, the control screen from the SUGV system was broadcasted onto a portable screen that was placed on the serious gaming laptop, as seen on the right laptop in Figure 19. The SUGV was placed out of sight from the participant. With all elements of the test in place, the researcher verified that the participant had steady video feed from the SUGV. Once confirmed, a researcher said, “We will do a count-down to initiate the next attention task and to press the autonomous button on the robot.” At the conclusion of the loud count down, the participant pressed the “Enter” button to initiate the attention enumeration task 2 and the WOZ began controlling the SUGV.

For Group A (iML), the WOZ controlled the SUGV in accordance with the decision points and behaviors as indicated in Table 5. For example, the SUGV departed from its start location and begin driving through the courtyard. Depending on the participants game-play, the speed increased or decreased as indicated in Table 5. Additionally, the path may vary depending on the participant’s “Search Pattern.” An orange box in Figure 30 represents where a cardboard box was located during the execution of this portion of the experiment. If the participant decided to search the box in gameplay, it was then searched in execution. The cardboard box and SUGV are shown in the left side of Figure 31. This trend continued for the entering and searching of each room within the objective building.

For Group B (aML), the WOZ controlled the SUGV identically for each participant at the same speed. The SUGV departed its start position, moved to interrogate the cardboard box and transitioned to “Peaky Mode.” This is shown in the bottom left of Figure 31. The SUGV then entered the objective building by first peaking inside. After initial entry, the SUGV continued to search the three other rooms in the objective building. Each room was searched the same fashion and order for each execution.

A researcher would wait until the participant was complete with the attention enumeration task 2 and would then ask the participant, “Are you prepared to send Marines into the objective building?” This question was not tied to the location and status of the SUGV. Once the participant said he would send his Marines to the objective building, that would conclude the live execution of the experiment.

6. Survey

After the live execution was complete, the participant answered the 12 questions of the Jian et al. survey. The survey was completed online. To transition to the survey, the display screen for the SUGV would be collapsed and the survey would be started on the serious gaming laptop. The researcher would enter the participant’s number and group into the survey. The participant would then begin on the instructions page shown in Figure 28. The conclusion of the survey would end the experiment.

Top Left: Shows the SUGV beginning its movement in the courtyard. The cardboard box for interrogation can be seen in the top of the photo. Top Right: Shows the SUGV just entering the courtyard. The only visible open door is the main entrance into the Objective Building. Bottom Right: Shows the initial room of entry within the Objective Building. Bottom Left: Shows the SUGV interrogating the cardboard box. In the forefront is a radio for the SUGV system. The picture is taken from the WOZ’s point of view.

Figure 31. Photos of the SUGV during Execution and Objective Building.

7. Reconsenting

Since deception was used during the execution of the experiment, each participant was reconsented after being debriefed and informed about the nature and specifics of the deception. Each participant was given the following brief: “In the past experiment there were three points of deception. 1. The robot was not autonomous. It was controlled by a gentleman behind the curtain. 2. Though you were provided the option to use the robot in remote control mode, that was not truly an option. 3. The video game did not record any data about your behaviors or intentions for how you wanted it to behave. If it was not evident, I'm researching on how to best develop trust between Infantry Marines and robots. This research will influence requirements for future Marines for Manned Unmanned Teaming. I thank you for your time and seriousness during this experiment." At this point, the participants reconsented to the use of their data.

E. DEPENDENT VARIABLES

The following dependent variables were collected:

1. Attention Enumeration Task Baseline Overall Time – The overall time from beginning to end of the attention enumeration baseline task. It does not include time to complete the tutorial.

2. Attention Enumeration Task Baseline Initial Reaction Time – The time it took from the red blocks appearing on the screen until the participant hit the "Space Bar" or the iteration timed out at 5000 milliseconds. This data did not include the tutorial times.

3. Attention Enumeration Task Baseline Input Time – The time it took from the program transitioning to the input screen until the participant pressed the "Enter" button or the iteration timed out at 5000 milliseconds. This data did not include the tutorial times

4. Items 1-3 of this list were recorded again for Attention Enumeration Task 2.

5. Length of Video Game Play – The total overall time each user played the video game to complete the training curriculum. Tutorial time is excluded from this data point.

6. Choice of SUGV Employment – A binary choice between remote control or fully autonomous mode.

7. Robot Count – The number of times the participant transitioned focus from Attention Enumeration Task 2 to the SUGV Screen. This was defined as a “look.”

8. Robot Look Time – The amount of time that attention was given to the SUGV Screen during a look.

9. Attention Look Time – The amount of time that attention was given to the Attention Enumeration Task 2 Screen during a look.

From the list above, 1-3 were all recorded via the Presentation Program. This data could also be analyzed by the number of blocks there were on the screen at one time. Five (5) was recorded by the GoPro Video. Six (6) was provided verbally to a researcher upon completion of the video game portion.

IV. ANALYSIS OF RESULTS

A. HYPOTHESIS 1

- There will be a greater proportion of Marines who will choose to use the "autonomous" robot over "teleoperated" in iML vs aML condition. ($p_{iML} – p_{aML} > 0$).

The aim of this hypothesis is to understand what sort of autonomous development Infantry Marines want to use as partners in MUM-T.

1. Statistical Analysis

A Two Proportions z-Test is the statistical method used to test this hypothesis. It is a one-way statistical method with an alpha level of 0.05. The assumptions and conditions for the test are: Participants randomly assigned to each group, <10% of the total population, two groups are independent of each other, Participants are independent of each other, Sample size 'success' or 'failure' is greater than 10. With the last assumption not meeting the required conditions, the Two Proportions z-Test will utilize the Fisher's Exact Test for comparison.

2. Results

The results indicated no significant difference in the proportion of Marines choosing to use autonomous mode in iML than aML approach with 63.1% (12/19) for iML, compared to 42.9% (9/21) for aML ($p = .167$).

B. HYPOTHESIS 2

- H2: There will be more indicators of trust for the iML than the aML conditions. ($\mu_{iML} – \mu_{aML} > 0$).

The aim of this hypothesis is to understand what sort of autonomous development Infantry Marines trust as partners in MUM-T through observable items. Based on the information developed within Chapter II, it is shown that the following factors would indicate trust:

1. Difference in Total Overall Time – Data point was produced via the attention enumeration task program.

2. Average Duration of Robot Screen Looks – Data point was produced by the Tobii Pro Lab using "Areas of Interests" within the program.

3. Average Duration of Attention Screen Looks – Data point was produced by the Tobii Pro Lab using "Areas of Interests" within the program.

4. Difference in Average Input Reaction Time – Data point was produced via the attention enumeration task program.

5. Difference in Average Initial Reaction Time – Data point was produced via the attention enumeration task program.

6. Looks at Robot Screen – Data point was produced by the Tobii Pro Lab using "Areas of Interests" within the program.

1. Statistical Analysis

A group of the factors that are used to support this hypothesis are the difference in performance standards between the attention enumeration baseline task and the attention enumeration task 2. To begin, outliers from the attention enumeration tasks were removed by using the Robust Fit Test for Outliers excluding data that was outside 2.5 standard deviations. Time recorded data is shown in Figure 32. All data points for attention enumeration tasks are in milliseconds. All three distributions show slightly negative kurtosis with minimal skewness.

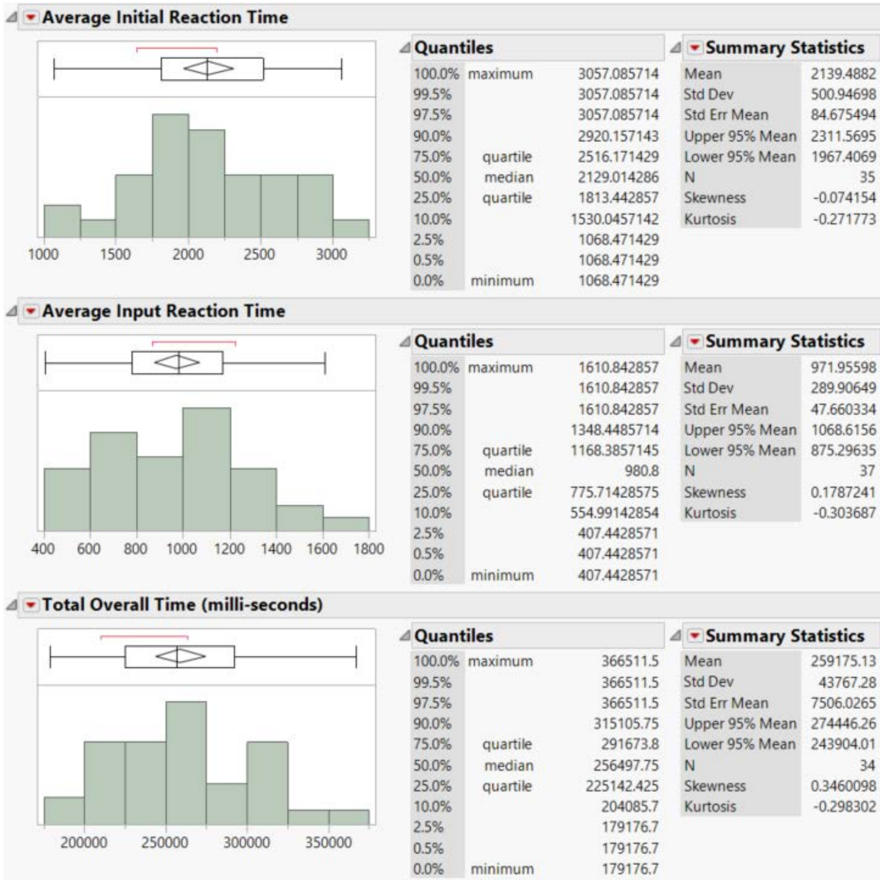


Figure 32. Attention Enumeration Task Baseline Time Recorded Data.

With the large number of data points, the data was binned for follow on statistical testing with the Multivariate Analysis of Variance (MANOVA) Test. If a Wilcoxon Test is required, it is due to the nonparametric distributions between comparison groups.

- Difference in Total Overall Time – Wilcoxon Test
- Comparison of Average Robot and Attention Times – MANOVA
    - Average Attention Time "Look"
    - Average Robot Time "Look"
- Difference in Reactions Times – MANOVA
    - Overall Input Reaction Average

- Overall Initial Reaction Average

- Robot Look Count – Wilcoxon Test

- Survey Results – Two Sample t-Test

The following sections describe the analysis for each of the major tests ran.

a. Difference in Total Overall Time – Wilcoxon Test

The data does not meet all the assumptions and conditions for a Two Sample t Test, due to lack of normality of data between the two groups. The two groups do a have a similar distribution, so the Wilcoxon Test was applied. The results are shown below in Figure 33. With this data point, a number closer to zero is desired. Closer to zero shows that participants were able to complete both the attention task and partnering with the robot closer to their baseline attention task time. A Wilcoxon Signed-ranks test indicated that the Difference in Total Overall Time for attention tasks was not significant from Group A (iML) (M = -92,876, SD = 123,331), to Group B (aML) (M = -54,434, SD = 77,451), Z = -0.717, p = .47, d = 0.373.

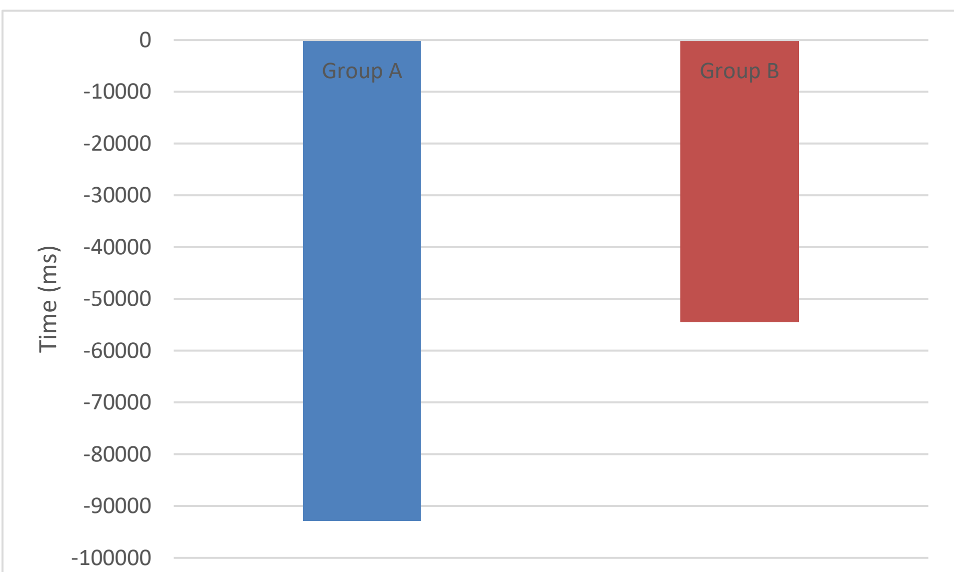


Figure 33. Difference in Avg Overall Time.

b. Comparison of Average Robot and Attention Times – MANOVA

For the comparison of average robot and attention duration per "look," the MANOVA test is used since the data points influence each other. The data meets all assumptions and conditions. Four data points were excluded as the participants looked only at either the attention task or the robot screen for the entire duration of the live portion of the experiment. Within this grouping of data, a larger average time spent on the attention task and lower average time spent on the robot screen is more desirable. The MANOVA test, graphs shown in Figure 34, fails to reject the null hypothesis as there were no significant differences between groups, $F(1,25) = .804$, $p = .459$, $\eta_p^2 = .060$.

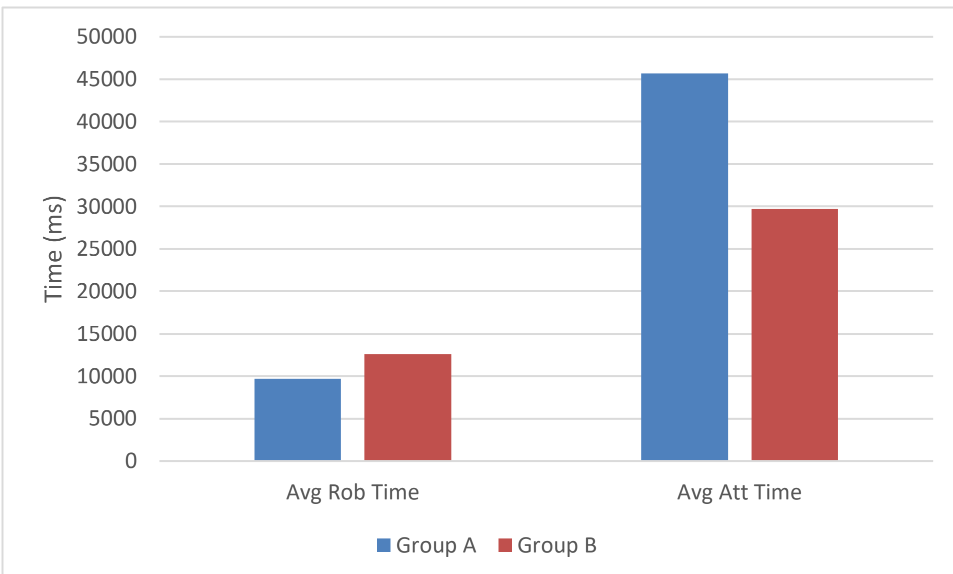


Figure 34. Average "Look" Times.

c. Difference in Reactions Times – MANOVA

For the difference in reaction times, five participant's data were excluded due the participants not following instructions on how to complete the attention tasks. With this data excluded, all assumptions and conditions for the MANOVA test are met. Figure 35 shows the bag graphs for Group A (iML) and Group B (aML). A value closer to zero is more desirable. The graph tends to show an overall difference between Group A (iML) and Group B (aML) data points, but the MANOVA test fails to reject the null hypothesis of an interaction between groups as there were no significant differences, $F(1,31) = 0.656$, p = .526, $\eta_p^2 = .041$.

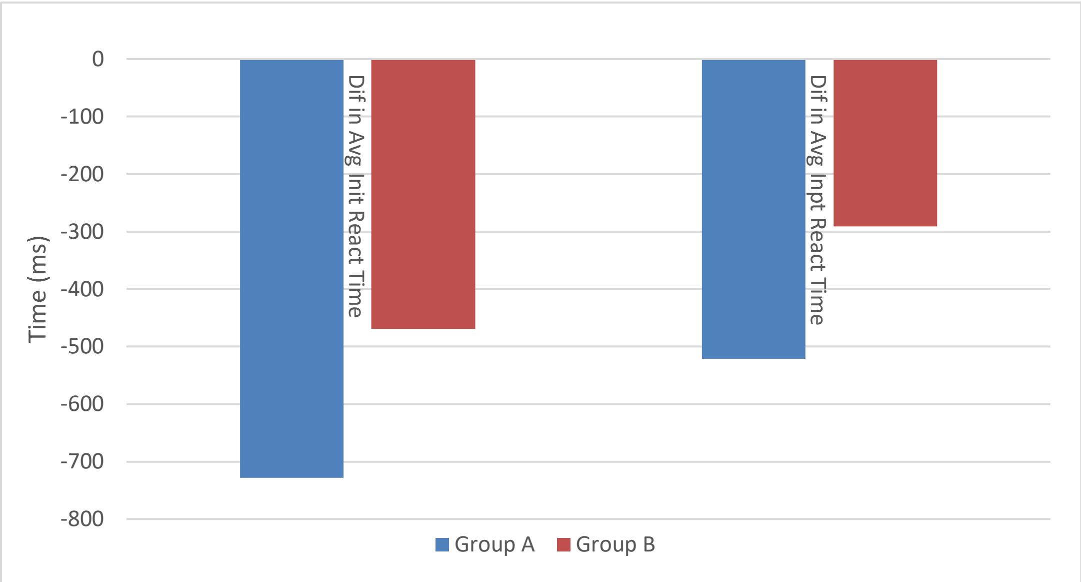


Figure 35. Difference Average Initial and Input Reaction Times.

d. *Counts Analysis – Wilcoxon*

A Wilcoxon Signed Rank test was used to analyze the robot looks count data. The data is non-parametric with similar distributions and meets assumptions for testing. The fewer looks at the robot is an indicator of greater trust. The Wilcoxon Signed-ranks test indicated that the number of "looks" at the robot screen was not a significant difference from Group A (iML) (M = 37.18, SD = 36.80), to Group B (aML) (M = 36.61, SD = 27.34), Z = -0.215, p = .817, d = 0.018, compared in Figure 36.

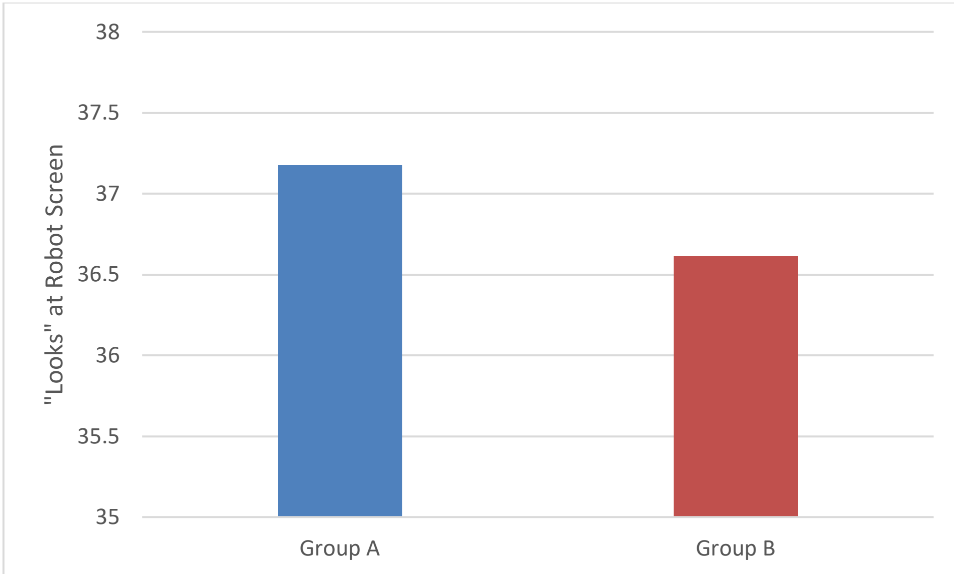


Figure 36. Count of "Looks" at Robot Screen.

e. Survey Results

Upon completing the live experiment, the participants completed the Jian Trust in Automated Systems Survey [71]. As this survey was completed by the participant post the live execution, it is not an indicator of behaviors, but the attitude of trust towards the system. The Two Sample t-Test fails to reject the null hypothesis as there was not a significant difference between trust survey scores from Group A (iML) (M = 4.79, SD = 0.181) to Group B (aML) (M = 4.96, SD = 0.172), $t(38)$ = 0.669, p = .746, d = 0.211.

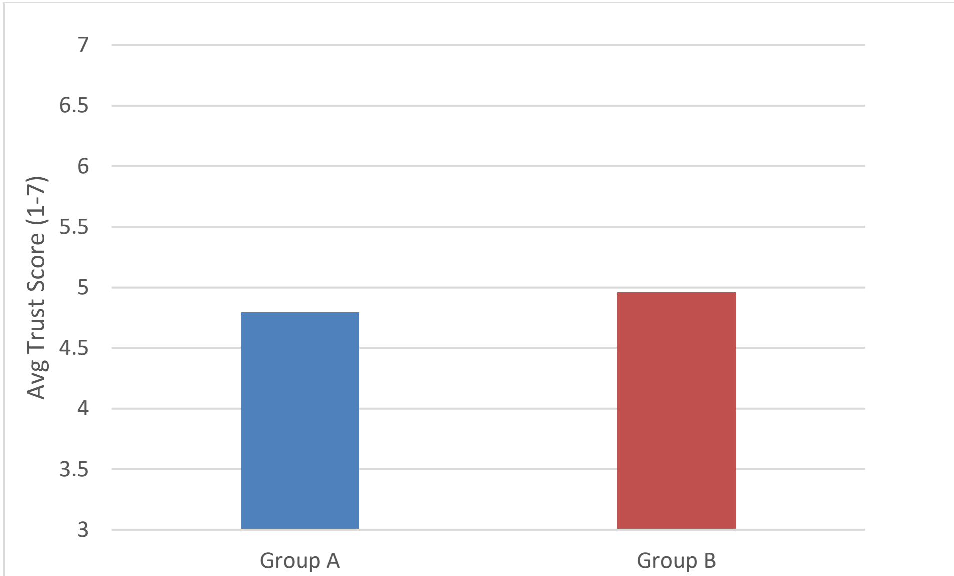


Figure 37. Trust Survey Avg Score.

2. Results

All recorded indicators of behavior and attitudes of trust between the two groups fail to reject the null hypothesis. Even while comparing trends between each statistical test for this hypothesis, there is no consistency. While analyzing the results, there appeared to be two factors that potentially influenced this hypothesis: 1. Too few participants. 2. Being "forced" to use the autonomous mode.

a. User's Preference

Though a Two Sample t-Test does not show a significant difference between trust survey scores of choosing "autonomous" mode (M = 5.04, SD = 0.168) to choosing "remote control mode" (M = 4.69, SD = 0.177), $t(38) = -1.47$, $p = .150$, $d = 0.373$, it can potentially be a confounding element. This data is shown in Figure 38. Speculations on this data point are covered in Chapter V.C. Future Work.

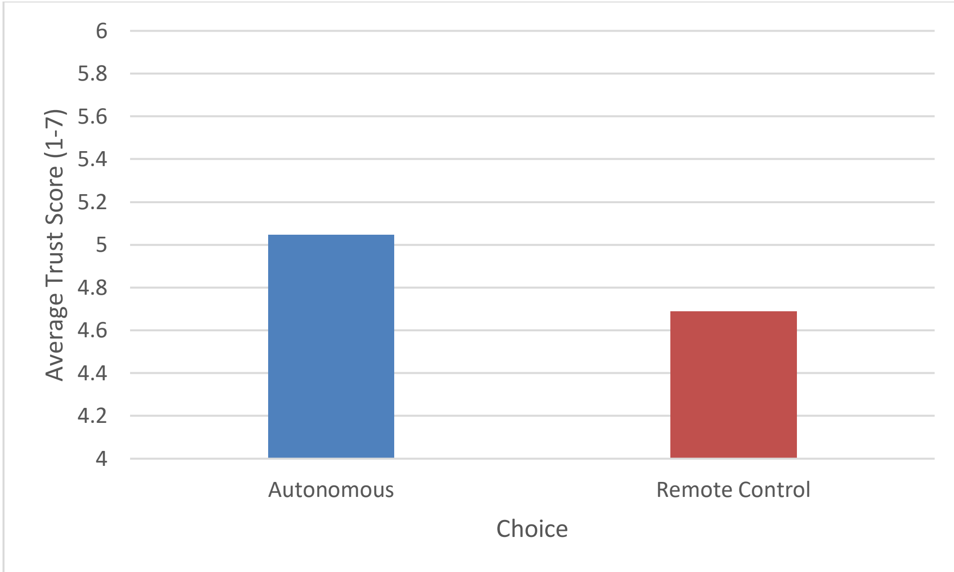


Figure 38. Choice Comparison on Trust.

b. Virtual Training Time

Only the visual displays on the user interface dashboard of the virtual training environment differed, as shown in Figure 25 and Figure 26. In exploring the idea of which group would invest more time in the virtual training environment, the assumption of Group A (iML) participants would invest more time in the virtual training environment than Group B (aML) participants. In reviewing the data of virtual training time, recorded in seconds; there was a significant difference between the groups. Virtual training times were higher for Group A (iML) (M = 1150, SD = 94.7) than for Group B (aML) (M = 898, SD = 70.6), t(15.55) = -2.05, p = .029, d = 3.017. This finding contributes to concepts introduced Section V.B.3. Use of Simulations for Serious Gaming.

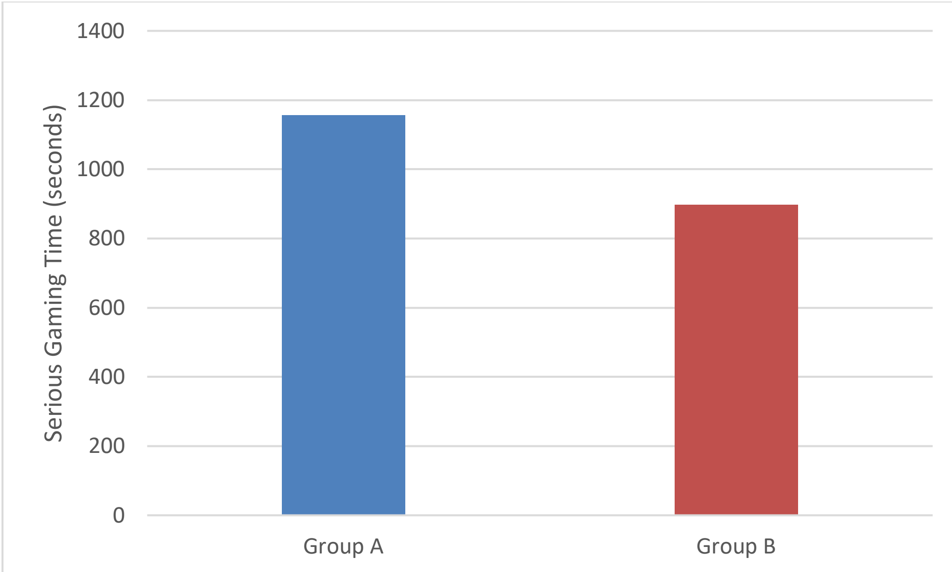


Figure 39. Virtual Training Time Comparison.

C. LIMITATIONS

Due to the experiment working in coordination with a training event in a TECOM curriculum, the research team was subject to the decisions by the AITB-E command. As important as the research is, the Marines participating in the training were days away from graduating and returning to lead infantry squads within the Fleet Marine Force (FMF). With an understanding of this prioritization, two days of the field testing were lost to training requirements and Camp Lejeune's closure due to weather. This resulted in only experimenting with 80% of the planned 50 participants. This lack of participants influenced the research and ability to use the theory of large numbers for data test points.

D. SUMMARY

Hypothesis 1 aimed to identify what sort of behavioral development for an autonomous agent Infantry Marines will prefer to have in their future unmanned teammates. The choice was between an autonomous agent or remote control for both Group A (iML) and Group B (aML). Group A (iML) developed the behaviors of their autonomous agent while Group B (aML) used a pre-programmed behavior. The participants made their decision after training in a virtual environment with the system. While there seems to be a trend, there is no significant difference showing that the participants would prefer to use an iML autonomous system over aML autonomous system.

Hypothesis 2 was directed at identifying which behavioral development process for an autonomous agent Infantry Marines will trust more. Reliance was measured by the difference between the baseline task and dual task performance in the attention enumeration task. Number of glances at the robot screen and duration of looks were recorded via the Tobii Eye Tracking system to measure the amount of time invested by the participant in the robot's actions. The attitude of trust was captured in the Jian et al. Trust Survey. There are no clear indications of a difference in trust between the groups.

All data points analyzed and assessed fail to reject both null hypotheses. A significant difference was identified in the amount of time spent in the virtual training environments with Group A (iML) spending more time. With the increased amount of time in the virtual training environment, an impression is given that the participants took the process of training the agent in the iML approach as a valid task. This impression may contribute to the number of glances and time looking at the robot screen that Group A (iML) took. Without the demonstration of the agent's behavior in a virtual environment prior to live execution, they utilized the live execution to observe the product of their training. Along similar lines, Group B's (aML) results may have been influenced by wanting to see the actual behaviors of the autonomous robot. Ideas around these findings and indications are further developed in Chapter V.

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V. CONCLUSIONS, RECOMMENDATIONS, AND FUTURE WORK

A. CONCLUSIONS

1. Trust within Manned-Unmanned Teaming

As research revealed by Lee and See [10] and Sheridan [62] showed, trust is an evolving attitude that creates a behavior of reliance. As trust evolves the previous actions influence the mental model and future trust, as shown in Figure 16 [62]. This trust control feedback loop ties to the MUM-T theory of *interdependence* from Johnson et al.'s perspective [54] with the following statements written from the human's perspective:

- I can assign (*Directability*) the correct (**Resolution**) task that the autonomous system was designed to accomplish (<u>Purpose</u>).
- The actions performed (*Predictability*) match my expected actions (<u>Predictability</u>) for the autonomous system (**Calibration**).
- The actions I observe (*Observability*) are performed (<u>Performance</u>) how I expected the autonomous system to complete the task (**Specificity**).

If all of these statements are true, then the human will have an intimate understanding and trust in the unmanned teammate in the same fashion that the United State Marine Corps portrays in its seminal document, *Warfighting* [58]. Idealistically, this occurs when the human's mental model matches the unmanned teammate's agent model. As justified by the research in XAI, this is nearly impossible to achieve. What is possible, through experiences as teammates, is for the human to have a mental model that can assess the inputs received by the unmanned teammate to anticipate the unmanned teammate's future actions. Moreover, by observing the actions of the unmanned teammate the human would be able to infer the inputs received to create those unmanned actions. Through pure interdependence the converse is also achievable. This would then create a common team model between both elements allowing for them to accomplish more than just the sum of its parts; the aim of MUM-T.

The only approach to achieve this level of intimacy, while still considering the limitations of training time and costs presented in Chapter I, are for the MUM-T to train in a virtual environment. The approach for an autonomous system produced through aML is for the human and the unmanned teammate to participate in virtual training together where the human controls the human's avatar and the autonomous agent controls the unmanned teammate's avatar. This could produce awareness of the autonomous agent's behaviors but does not allow for adaptation or tailoring of the autonomous agent's behaviors to human's directions and guidance. The alternate option is iML.

2. Interactive Machine Learning (iML)

The literature review for this research shows that iML is a viable option for agent behavior development for unmanned autonomous teammates within a MUM-T. The impetus for most of the reviewed research is focused on a better understanding and familiarity with the agent by the end-user. Highlights of iML brought together within this research are:

- The user can develop a mental model of the agent's behaviors [45].
- The agent develops a mental model of the user's behaviors [45].
- Understanding of the uncertainty of an agent's behaviors correlates to better understanding the expected performance of the agent [63].
- Agents developed within iML techniques have an intrinsic link to their "instructors" [12].
- Agents learning improved as "instructors" demonstrated desired behaviors [65].
- Agents developed within iML techniques have an easily identifiable behavior [44].

Building from the outlined benefits, *Warfighting*, announces that experiential learning is a critical element in developing familiarity within a relationship [58].

Supporting this concept, *Tactics* acknowledges that experiences cannot be gained simply through war, but can also be made through serious games like "tactical decision games, sand table exercises, war games, field exercises, and rehearsals" [61]. Team experiences build familiarity and confidence which in turn produces trust [58].

B. RECOMMENDATIONS

1. Operational Testing

The ability to test and interact with FMF Infantry Marines was beneficial for all parties involved. The feedback and discussions with the participating Infantry Marines and the AITB-E staff was advantageous in refining the concepts of serious gaming and unmanned teammate system requirements; and balancing academic research of NPS to the realities of the FMF. Although our results did not show statistical significance, potentially due to a reduced number of participants, the experiment was still beneficial as it exposed Infantry Marines to research to improve their combat effectiveness.

The 38th CPG directs that outside entity experimentation with the FMF be nested within MCWL's larger experimentation process [1]. To achieve this direction for NPS Students, greater flexibility and broader experimentation criteria is needed from MCWL. Within the 24-month cycle of the standard master's degree, there is limited ability for a thesis research topic to be innovative and challenge status quo if it is required to be nested within prescribed ongoing topics. A proposed solution that can create focus from MCWL is to create a spring and fall experimentation season. Within those two seasons, an infantry unit can be placed in direct support of MCWL for experimentation. This allows for MCWL to maintain clearance authority for the experimentation while preserving innovation thrusts from outside agencies with minimal impacts to the FMF.

2. Unmanned Teammates and its AI Agent

The unmanned ground teammates within MUM-T at the Marine Corps Infantry Squad level must be autonomous with the ability to learn. By the definitions used throughout this research, this would be autonomy with AI. The ability to learn, recognize patterns, and adapt is crucial. Adaption is a critical element in war and both human and unmanned teammates are required to adapt for success on the battlefield [61]; a purely autonomous system will lack the ability to learn from new situations and environments.

The unmanned teammate should come to the human equipped with a baseline of autonomous actions, e.g. obstacle observance, facial recognitions, and understanding of basic infantry techniques and procedures. A serious game should be used for development of advanced features, tactics, and the human's preferences of the AI agent of unmanned teammate. During serious gaming is when the AI agent should learn and evolve through iML techniques. The iML techniques will incorporate recorded data, voice after action reviews utilizing ITL techniques, and patterns from both the live and serious gaming environments. Prior to the AI agent being produced from the iML algorithms, an execution of the agent's autonomous behaviors will be rehearsed virtually with the human. This will allow for a refined mental model of the unmanned teammate's behaviors for live execution, thus increasing the trust and familiarity with the system.

To provide a concrete example of the types of behaviors the human should develop within serious gaming, a table produced by recent NPS research is used. Utilizing Johnson et al.'s Coactive Design Process [54], USMC Captains Franco and Spada's [22] research focuses on interdependence within MUM-T and how to command and control with unmanned teammates. Within their research, they used an interdependence analysis table for how an EMAV and human would occupy a machine gun support by fire (SBF) position, Table 6. The concept of an interdependence analysis table was presented by Johnson et al. [74] as a process for maximizing the HABA-MABA model for MUM-T tasks. [22] and [74] advocate that this analysis process should be used for developing all of the possible tasks for a MUM-T and to decide who is best suited to perform the sub-tasks. Table 6 was modified with the "Black Stars" next to the "decision points" delegated to the EMAV for its own non-lethal decisions. Examples are position and speed of movement within relationship to the human. An obvious and quick retort would be to allow the human to "control" those preferences during the execution. This would then relegate the human as a controller and fail to maximize the benefits of MUM-T. [22] and [74] research does not reveal how the autonomous vehicle should develop the reasoning to make those decisions, but these are the exact types of behaviors that should be developed and controlled by the human.

Table 6. Interdependence Analysis Table for Movement to a Support by Fire Position. Adapted from [22]

				Performer	Supporter	Performer	Supporter	Machine					Human		
	Milestones	Tasks	Subtasks	EMAV	Human	Human	EMAV	Automation				Interface			
								Camera	LIDAR/GPS	Track Control	.50 Cal Machine Gun	Kilswitch	Perception	Cognition	Action
Movement to Support by Fire Position	Movement to SBF Position	Identify formation for movement	N/A												
		Get into decided formation ★	Input Follow mode												
			Sense teammate position												
			Interpret proximity												
			Decide position in formation												
			Move to position												
		Maintain dispersion throughout movement ★	Sense teammate position												
			Interpret teammates speed												
			Decide appropriate speed												
			Execute speed												
		Danger Zone Avoidance ★	Sense danger zone parameters												
			Interpret if danger zone is avoidable												
			Decide to Avoid or Proceed												
			Input Avoidance Command												
			Execute Avoidance												
		Obstacle Avoidance ★	Sense obstacles												
			Interpret if obstacle is passable												
			Decide to avoid or proceed												
			Execute avoidance												
		Halt movement prior to SBF position ★	Sense teammate position												
			Interpret proximity												
			Decide position in formation												
			Execute Halt												

3. Use of Simulations for Serious Gaming

Some uses of virtual environments for training take the form of serious gaming. The TDKs purchased by the Marine Corps is a prime example of this use case. As the USMC continues to invest in virtual environments for training, they must also invest in the development of virtual models for each unmanned ground teammate. The virtual models need to be built to operate within the Marine Corps' LVC-TE. Within the virtual model, there must be three options for the unmanned teammates virtual model's avatar control: 1. A human controls the avatar to learn the capabilities and limitations of the system. 2. A human controls the avatar as an example for follow on "supervised" ML techniques. 3. Autonomous mode with a human "Positive" or "Negative" reward button to allow for "reinforcement" ML techniques. Options 2 and 3 encapsulate the concept of iML. Utilizing the concept of occupying a SBF, the three different user modes are explored.

1. User Full Control Mode - In this form, the human is controlling all aspects of the unmanned teammate in the virtual environment. This sort of serious gaming will enable the human to learn the capabilities and limitations of the unmanned teammate. In the

serious game, the human could explore the SBF position from the perspective of the unmanned teammate. It would show the human a realistic view, trafficability, lines of sight, and rates of movement. These perceptions would refine the human's mental model of the unmanned teammates perspective of the situation.

2. Example User Control Mode - This form will serve as the "Performance Standard," reference Figure 6, for supervised ML techniques. In this form, it will take two humans to create the example. One to control the human's avatar and the other to control the unmanned teammate's avatar. Once the scenario is executed in the virtual environment, the scenario and both behaviors will be exported for development in a separate module with supervised ML techniques. The module then runs millions of iterations of similar scenarios to develop the autonomous behaviors. These iterations can still have exploratory steps to allow for presentation of "novel AI" solutions. Upon completion of the ML, the human is presented with three agents for the unmanned teammates behaviors. After reviewing a demonstration of each behavior in the scenario, the manned teammate then decides on the agent to use.

3. Reinforcement User Control Mode - The final form of control mode is for minor corrections and developments of the agent's behaviors. While the human controls the human's avatar, the agent will control the unmanned teammate's avatar. This form will serve as a virtual rehearsal. As the team rehearses the occupation of a SBF, the human will have the opportunity to provide positive or negative reinforcements at the decision points outlined in the interdependence analysis table. For example, if the agent places itself in the right position of the formation, the manned teammate can provide a positive reward to reinforce that good behavior.

Additional benefits from this serious gaming is the pro-active approach a human can have with training their own unmanned teammates' agent and an understanding of the agent's training progression. A common phrase within the Marine Corps is that Marines accomplish more with ownership. The assignment of an agent's behavior to a Marine will create a greater value and connection with the agent, vice if being assigned from someone else. The data of time spent in the virtual environment training supports this point as indicated in Figure 39 in Section IV.B.2.b. Virtual Training Time. This theory is presented succinctly by Gutzwiller and Reeder [75] in their 2020 research: "The IML approach further allows the user to be the designer, as Muir (1994), suggested, which is likely to improve trust in ML. In parallel, the "IKEA effect" also suggests that the experience of building these control models via interaction may impart an increased valuation to them (Norton et al., 2012) which may be a prophylactic against their disuse." Continuing with the thread of disuse and misuse, the human owns the training curriculum for the agent. This ties directly to calibrating trust due to the resolution of the human's understanding of the training curriculum. The human can expect greater uncertainty in the unmanned teammate's performance for tasks not trained or in new environments. As Zhou and Chen indicated, understanding uncertainty can positively influence trust [63].

4. Implementation of MUM-T into an USMC Infantry Battalion

As referenced in Section I.C, a brief synopsis of Figure 40 follows. The cycle, and focus of my research, begins in the top left corner. In this stage, an Infantry Marine is given a robot with a removable AI device (RAID) and a compatible game console. The RAID is the "brain" of the robot. The RAID is preloaded with a baseline of automation that mimics the baseline of knowledge gained by Marines at the School of Infantry prior to arriving at their first Infantry Battalion. The game console, capable of establishing a connection with the RAID and the LVC-TE, is used by the Marine to interactively train with his robot in a virtual environment. The RAID is capable of the requirements defined in previous sections of this chapter. Due to the previously mentioned garrison restraints, the robot's physical hardware lives in the "RoboPool."

When it is time for live training or operations, the Marine installs his RAID into his robot. Now, the functioning robot and Marine have become a live team with calibrated trust and tendencies built within a simulated environment. Upon completion of the live task or operation, the Marine conducts an after-action review (AAR) with his robotic teammate. This may be accomplished through hasty or deliberate means. A hasty AAR could be conducted by voice ITL with the robot to provide critiques on task completion and team interactions. A deliberate AAR, time and situation permitting, could be conducted through the game console, allowing for a full three-dimensional digital critique and wholistic AAR process.

Once the next mission is received, the S-2 – intelligence section – will create a virtual future operating environment by inserting the most likely adversarial agents into the virtual model of the physical world captured through unmanned aerial vehicle footage and photogrammetry. Building on previous shared experience and training, the team, Marine and Robot, will then conduct wargaming and mission-specific training prior to the next live operation. The area of this research is shown by the yellow star in Figure 40. Appendix A shows other research conducted by the Office of Naval Research (ONR) Code 34 that influence this model.

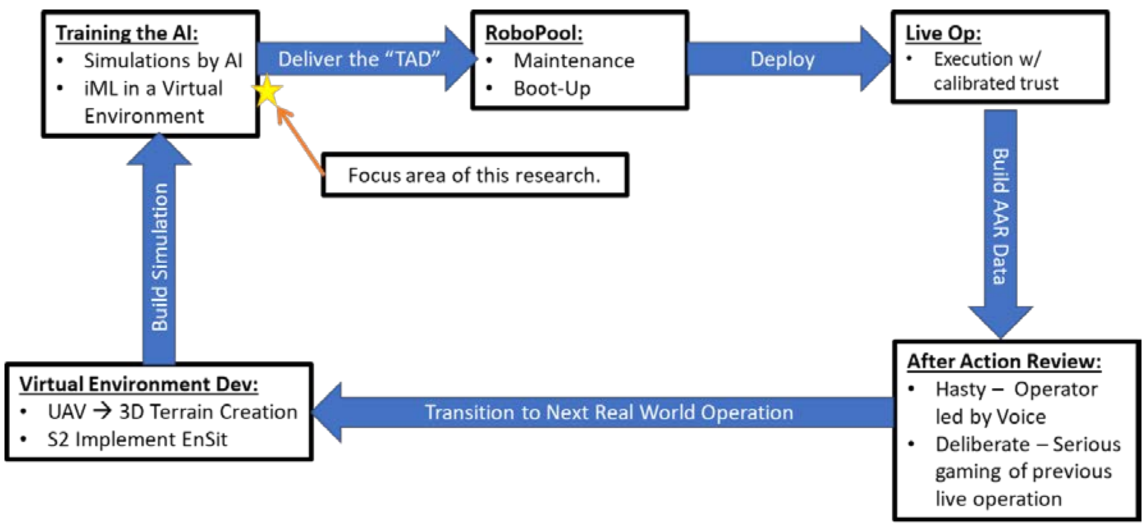

Figure 40. Conceptual Model of Future Autonomous System Cycle.

C. FUTURE WORK

1. Experimental Redesign

The ability to demonstrate the autonomous behaviors in a virtual environment for this experiment was lacking. A playback of autonomous behaviors will aid in the refinement of the human's mental model. In the event of this research, the mental model of the behaviors was developing as the participant was attempting to complete another attention enumeration task. While identified during planning, game development, and experimental design, there was not a viable option to produce a reasonable iML autonomous behavior. In future research while utilizing a "WOZ" type of construct, a multitude of different playbacks of iML autonomous behaviors can be developed. After observing the participants desired behaviors in the virtual environment, the participant can be shown a specific playback to match the participant's preferences. This could create a better perception of iML.

Within the experimental design, the choice for the participant to decide the type of control to have on the robot, either remote control or fully autonomous, may have revealed a confounding factor on trust. While analyzing the data point of difference of trust between the options, there appeared to be a potential growing trend. Two potential reasons for this possible trend are: 1. The response from the researchers concerning the "broken" remote control for the teleoperated mode may have degraded the trust in the required use of autonomous mode for the participant. 2. The participant approached the autonomous system with a lower level of trust, and this lower level of trust caused the user to choose the "remote control mode." In turn, the participant's trust in autonomous systems remained lower throughout the experiment. Recommended ways to prevent this possible confounding factor would be to remove choice from the design of experiment and replace it with a survey question following the completion of the autonomous testing. An additional option is to add a pre to post trust survey to identify change in trust at the expense of potentially biasing the participants.

With trust being the "attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability" [10], the next experimental design should increase the amount of vulnerability that the participant feels during the dual task paradigm. This research relied directly on the participant's desire to do well during the dual task time. There was no known punishment, negative outcome, or loss if the participant did not trust the robot in its reconnaissance task. An approach to improve this in future research is to incorporate a competition aspect to the experiment or to provide the impression of a negative reward following a poor execution in both of the dual tasks. These two actions would influence the individual’s desire to achieve a goal or feeling of vulnerability.

2. Autonomous Agent Creation

All aspects of autonomy were controlled by a WOZ. As this research serves as the initial thrust of transferring trust of autonomous behaviors from virtual to live environments, the next logical step is for the development of autonomous agents that meet the experimental design requirements. There are pre-programmed autonomous agents that exist in both virtual and live environments. The missing link is the ability to create an autonomous agent via the iML technique in a virtual environment to transfer to a live environment.

To test with a similar demographic while developing the behaviors through the iML approach would require daily on scene contact, or the ability to have daily remote access. A potential solution for the remote based access is to develop a web-based gaming application. Utilizing the concepts presented in Section V.B.3. Implementation of MUM-T into an USMC Infantry Battalion, participants would log-in to execute a single level of the curriculum per day. After the completion of the level, the agent would enter the supervised ML algorithms within the remote ML computers. Once the behaviors are developed, the participant can log-in to see the three created behaviors and make the selection of the desired agent. This would continue until the training curriculum is complete. At this point, the agent can be exported for actions with an autonomous robot.

3. Virtual Environment Development

The virtual environment used for serious gaming did not have any ML attributes connected to it. The next step for the virtual environment is to model it in a fashion that supports ML parameters. To create an agent that functions in all environments, the results of the agent’s sensing capability must be matched in both live and virtual environments and used as inputs for the ML algorithms. For example, the ability for the agent to assess a doorway must match in both environments. Within the ML algorithms, distance to doorway will need to be used to drive autonomous behaviors. As robotics experts have already proclaimed, this will be a major undertaking [19].

D. SUMMARY

This research sought to explore trust and its development in a virtual environment and how it transferred to live execution between groups with different approaches to autonomous behavioral development. The two-group design analyzed aML against iML in a dual task paradigm. Though the number of participants did not produce statistically significant results, the attention enumeration task and dual task paradigm established a testing environment where indicators of trust were easily measurable.

The results were not statistically significant, but the main impression from this research is Infantry Marines may want to use an iML system over an aML. There are no indications on which type of system they would trust more though. A statistically significant point shows Infantry Marines invest more time training in a virtual environment during an iML approach vice for familiarity training with an aML system.

The literature review culminated to reinforce that iML is a viable approach for developing better MUM-T. This research was inconclusive in determining if the iML technique increases trust. Refining the experimental design and testing with a greater number of participants will yield better results on the indications of trust.

Though the results of this study are inconclusive due to a limited number of participants, future research should continue to explore the concept of using serious games to enable an iML approach for developing agent behaviors for an autonomous teammate. Future research will inform actions and decisions to increase the efficiency within a MUM-T. The ability for each member of the MUM-T to develop a common mental model for each member will be critical. The developed mental models and performance of each teammates' actions will build greater trust. With a virtual training environment, cost and maintenance requirements will decrease while developing mental models, behaviors, and trust through a wide variety of training scenarios will increase. With the capacity to transfer the developed trust and agent from a virtual to live environment, the MUM-T can achieve greater effectiveness in tasks. In turn, our efforts can provide the warfighter a tailorable system that increases their lethality through trust and teaming.

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APPENDIX. ONR CODE 34 RESEARCH

ONR Code 34 | **S&T OPPORTUNITY** | September 2019

DeepAgent

AT A GLANCE

WHAT IS IT?

DeepAgent is a system that automatically learns realistic behaviors for entities in complex simulation environments using deep reinforcement learning.

HOW DOES IT WORK?

DeepAgent uses neural networks to estimate the future reward and best action given the current simulation state. These neural networks are improved by playing against existing other neural networks or by observing human players.

WHAT WILL IT ACCOMPLISH?

DeepAgent will simplify the process of developing complex behaviors in simulations. Rather than having an artificial intelligence expert manually encode domain knowledge from a subject matter expert, DeepAgent will automatically learn behaviors through a combination of self exploration and observations of humans.

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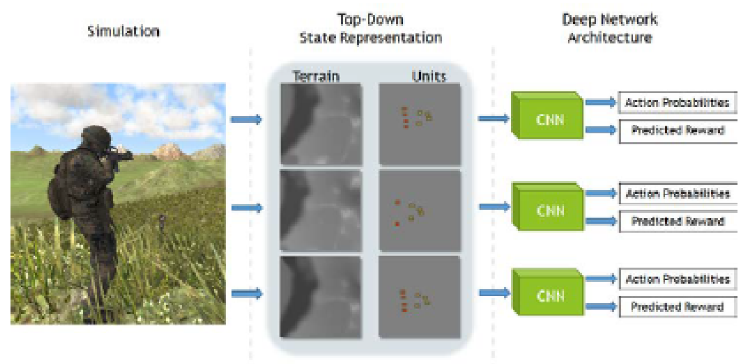
Work for this effort is performed by Soar Technology under ONR contract N68335-18-C-0539.



Training simulations enable warfighters to develop skills without putting their safety at risk or incurring costs typically associated with training such as fuel, munitions, etc. Unfortunately, simulations used for infantry training require additional operators to control friendly and enemy units which limits their ability to train unit leaders. By replacing operators with artificially intelligent agents (AIs), the cost and logistical challenges of training individual users is reduced and simulation-based training can be focused on higher echelon users. Artificially intelligent agents are typically time consuming to develop, requiring an AI expert and subject matter expert. DeepAgent aims to automatically learn these AI agents using deep reinforcement learning. This approach offers a number of benefits over hand coding AI agents:

- **Complex behaviors.** Deep networks can learn complex behaviors without any prior domain knowledge by playing in simulation (e.g. AlphaGo learned to play Go better than human professionals).
- **Novel strategies.** AI agents can explore novel strategies that were never taught to them by a subject matter expert. These strategies may be more effective than those used by humans.
- **Lower cost.** Training an AI agent using deep reinforcement learning does not require a subject matter expert to define the behavior and an AI expert to program the behavior.

On this effort, we are developing algorithms to support automatically learning behaviors using deep reinforcement learning in training simulations. DeepAgent has learned behaviors across a variety of domains including first-person Unity simulations, Atari, and Starcraft. The system supports training using multiple algorithms, deep network architectures, state representations, action representations, and simulation environments. In addition to learning through self exploration, DeepAgent will use imitation learning to learn through examples provided by humans.

Research Challenges and Opportunities:

- Evaluate and improve on state of the art deep reinforcement learning algorithms
- Develop state and action representations for first person-shooter training simulations
- Incorporate human examples into the AI agent learning process

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Figure 41. DeepAgent Data Sheet. Source: [76].

ONR Program Code 34 **S&T OPPORTUNITY** September 2019

STATE: Simulated Teachable Agents for Training Environments

AT A GLANCE

WHAT IS IT?

STATE is a system for creating intelligent, adaptive agents and generating virtual terrain for Small Unit Decision-Making (SUDM) simulated training environments.

HOW DOES IT WORK?

- A Virtual Terrain Procedural Content Generator enables rapid creation of large numbers of virtual terrains over which Red Force agents learn to reason
- A Behavior Engine implements agent perception and action based on principals of recognition-primed decision making
- An Agent Behavior Learning Engine optimizes agent behavior using simulation data and feedback from instructors

WHAT WILL IT ACCOMPLISH?

- STATE will support SUDM training developers through effective and cost-efficient terrain generation and implementation in simulation-based environments
- STATE will support SUDM training through intelligent allies and adversaries in training environments

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Work for this effort is performed by Charles River Analytics, Inc., Cambridge, MA, under ONR Contract# N00014-18-C-2053.

Training simulations that currently support Small Unit Decision-Making (SUDM) training are laborious to configure and expensive to manage with live personnel, which results in training that is limited in scope. Current simulations require numerous training instructors, called "pucksters," to configure and control simulated scenarios and entities, driving up the manpower costs of conducting simulation-based training.

The goal of STATE is to reduce the cost of simulation-based SUDM training by creating on-demand virtual terrain and software agents that act as pucksters.

Simulated Teachable Agents for Training Environments (STATE) features:

- A Virtual Terrain Procedural Content Generator to create a robust testing environment for virtual agents
- A terrain-reasoning application programming interface (API) to enable agents to perceive the terrain and environment, build situation awareness, and act.
- A Behavior Engine that implements agent perception and action based on principals of recognition-primed decision making
- An Agent Behavior Learning Engine that incorporates Deep Reinforcement Learning Bayesian reasoning, and Monte-Carlo Tree Search to configure agent parameters

Creating intelligent, adaptive computer-generated force technology for virtual training is especially challenging in the Marine Corps operational context. The pace, proximity, and range of possible offensive and defensive actions in Small Unit operations induces very challenging complexity in modeling requirements. STATE meets this challenge by providing a suite of tools that empowers trainers to improve agent behavior via automated learning and scales to meet future training needs at low cost.

RESEARCH CHALLENGES AND OPPORTUNITIES:

- Establishing sufficient variation in virtual terrains to support the evaluation of agent learning algorithms
- Implementing agent-based terrain reasoning, perception, and behavior that supports accurate modeling of components of Marine SUDM information gathering, situational assessment, and decision making
- Designing for integration with ONR S&T areas such as the Decision Making Learning Management System (DM-LMS) for inspection by Marine Corps Instructors and Leaders, and the Simulation Tailored Training and Assessment (ST2A) framework to direct agent behavior and provide scenarios for testing and execution

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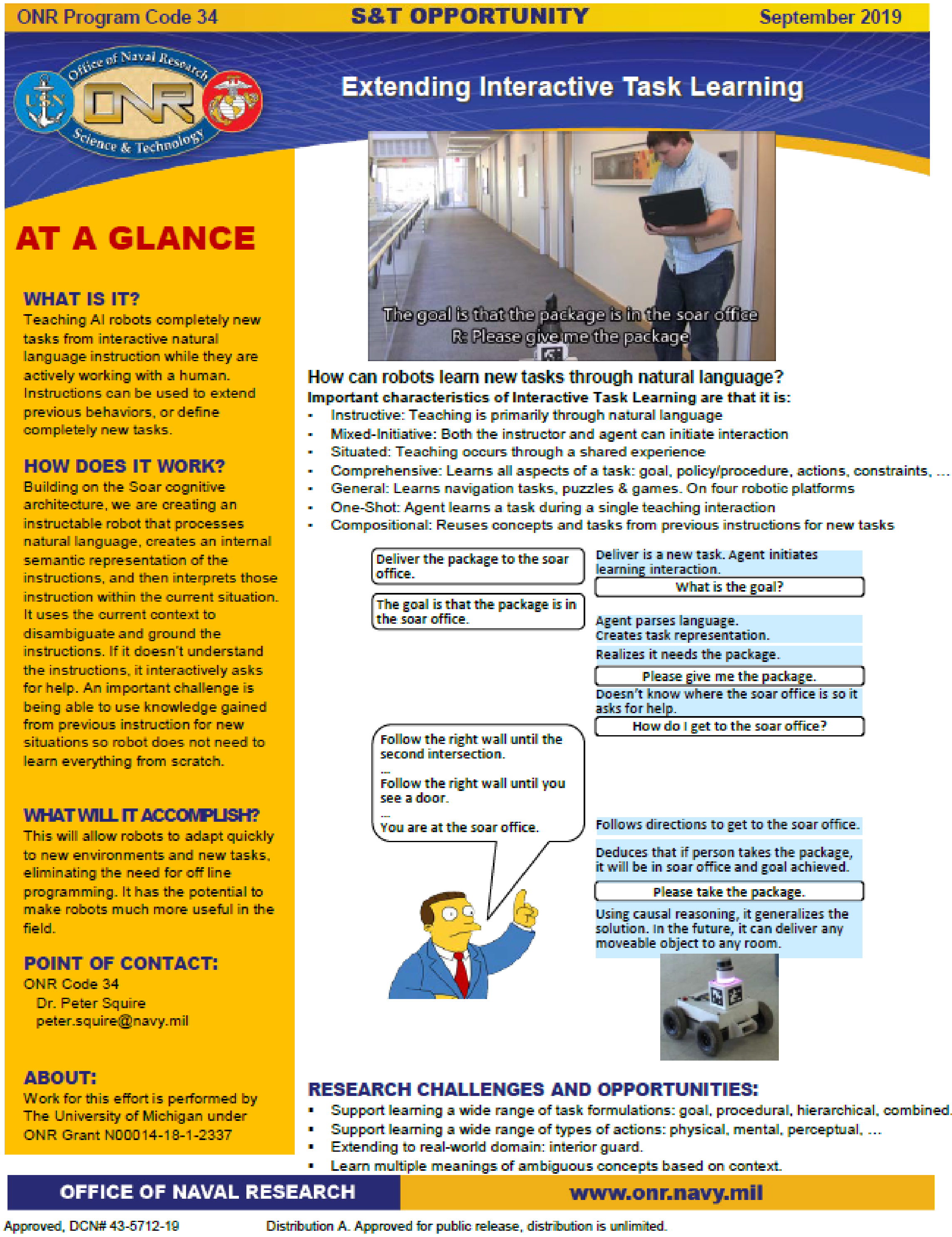
Figure 42. Simulated Teachable Agents for Training Environments Data Sheet. Source: [76].



ONR Program Code 34 S&T OPPORTUNITY September 2019

Extending Interactive Task Learning

The goal is that the package is in the soar office
R: Please give me the package

AT A GLANCE

WHAT IS IT?
Teaching AI robots completely new tasks from interactive natural language instruction while they are actively working with a human. Instructions can be used to extend previous behaviors, or define completely new tasks.

HOW DOES IT WORK?
Building on the Soar cognitive architecture, we are creating an instructable robot that processes natural language, creates an internal semantic representation of the instructions, and then interprets those instruction within the current situation. It uses the current context to disambiguate and ground the instructions. If it doesn't understand the instructions, it interactively asks for help. An important challenge is being able to use knowledge gained from previous instruction for new situations so robot does not need to learn everything from scratch.

WHAT WILL IT ACCOMPLISH?
This will allow robots to adapt quickly to new environments and new tasks, eliminating the need for off line programming. It has the potential to make robots much more useful in the field.

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Work for this effort is performed by The University of Michigan under ONR Grant N00014-18-1-2337

How can robots learn new tasks through natural language?
Important characteristics of Interactive Task Learning are that it is:
- Instructive: Teaching is primarily through natural language
- Mixed-Initiative: Both the instructor and agent can initiate interaction
- Situated: Teaching occurs through a shared experience
- Comprehensive: Learns all aspects of a task: goal, policy/procedure, actions, constraints, …
- General: Learns navigation tasks, puzzles & games. On four robotic platforms
- One-Shot: Agent learns a task during a single teaching interaction
- Compositional: Reuses concepts and tasks from previous instructions for new tasks

RESEARCH CHALLENGES AND OPPORTUNITIES:
- Support learning a wide range of task formulations: goal, procedural, hierarchical, combined.
- Support learning a wide range of types of actions: physical, mental, perceptual, …
- Extending to real-world domain: interior guard.
- Learn multiple meanings of ambiguous concepts based on context.

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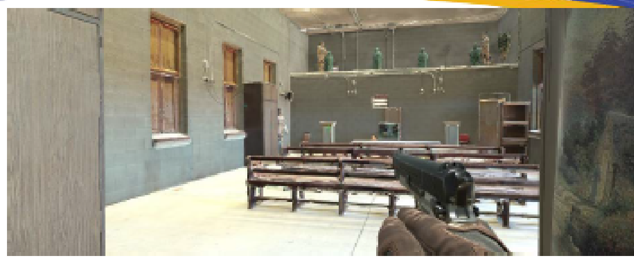
Figure 43. Extending Interactive Task Learning Data Sheet. Source: [76].

ONR Code 34 | **S&T OPPORTUNITY** | September 2019

Rapid Synthetic Environment Tool: Low Cost Virtual Training



AT A GLANCE

WHAT IS IT?

RSET is a software platform used to reduce the time and technical costs associated with producing virtual training environments of building interiors. By streamlining the process used to generate simulations, users with limited expertise will be able to build, augment, and train in virtual environments based off real-world 3D scans.

HOW DOES IT WORK?

• A 3D Scan is captured from a real-world environment. RSET is scanner-agnostic.
• The captured 3D data is run through an improvement algorithm to identify key features useful to the simulation engine. This improved data is loaded into RSET.
• Users can swap between 3D data sets, connect multiple scans together, add features to the 3D data, explore the environment on a desktop or in VR, run force-on-force simulations, and more.

WHAT WILL IT ACCOMPLISH?

RSET reduces the time and technical skill required to generate simulation environments by using 3D scanning. It makes simulation use available to more Warfighters by automating the workflow used today. It also expands the available tools used to interact with and train in these environments.

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Work for this effort is performed by Enomalies, LLC under ONR Contract N00014-16-C-1001

Virtual training environments offer endless opportunities for the Warfighter to train and familiarize themselves with a variety of scenarios and locales. While significantly less expensive than training in physical environments, virtual training still requires the use of a specialized team well-versed in 3D game engine development, mesh editing, and data optimization. When attempting to replicate a real-world environment within a virtual training engine, the required skill increases even further.

Objective
To reduce the time and technical costs associated with the creation of virtual training environments modeled after real world locations, thereby enabling Warfighters with limited technical experience the ability to create, modify, and interact with simulation environments in the most advantageous circumstances.

Enomalies' Rapid Synthetic Environment Tool (RSET) is a suite of software solutions and services designed to overcome the challenge of simplifying terrain data capture and import into a simulation engine.

The usage scenario for RSET is described below:
• 3D Scanning – To create an environment based off a real-world location, data about that environment must be captured. RSET is designed to be "scanner agnostic", meaning a wide variety of scan methods can be employed to capture that data. Enomalies has developed a specialized pipeline to turn regular cell phone and action cam photos and videos into explorable meshes via photogrammetry (Structure from Motion).
• Mesh Improvements – A hands-free algorithm used to improve the mesh will extract useful data from the captured 3D environment, such as doors, lights, and furniture. This information will be used to help tailor the game engine to the training-specific requirements.
• Simulation – The improved mesh is loaded into RSET, where users can explore the space, design AI simulations, run multi-player encounters, or augment the captured environment with their own 3D objects and renders. Enomalies has received positive feedback from school administrators and local police departments regarding RSET in its private sector use as a school safety and training tool.

RESEARCH CHALLENGES AND OPPORTUNITIES:

- After-Action Review tools used to pull meaningful training data from videos/photos used in the Structure from Motion Pipeline.
- Expand SFM Pipeline functionality to increase scan fidelity using trained AI models
- Networked force-on-force simulations with modification tools built in.
- Interior Position Reckoning to determine rough interior location of user in previously scanned structure

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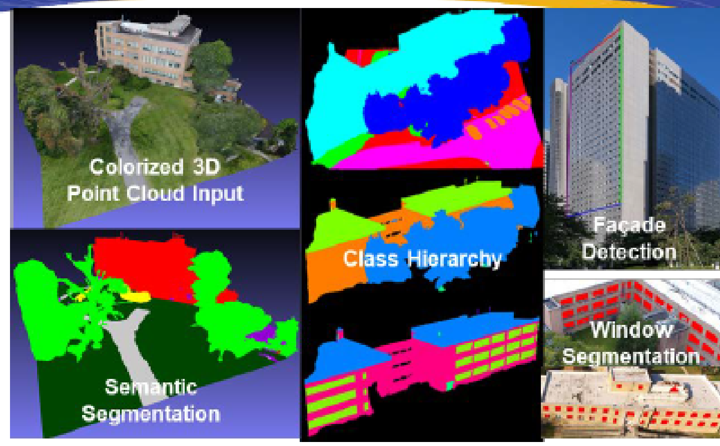
Figure 44. Rapid Synthetic Environment Tool: Low Cost Virtual Training Data Sheet. Source: [76].

ONR Code 34 **S&T OPPORTUNITY** September 2019

Layered Semantic 3D Modeling from Large-Scale 3D Point Clouds for Indoor and Outdoor Environments



AT A GLANCE

WHAT IS IT?

- A hybrid 3D segmentation pipeline to obtain rich, hierarchical semantic attributions for 3D point cloud data
- Mixes neural networks with domain knowledge and common-sense rules
- Jointly processes 2D images and 3D data for complementary cues
- Fills in missing data using contextual information learned from training data
- Assigns class labels to different objects, parts and terrain areas in a coarse-to-fine fashion

HOW DOES IT WORK?

- 3D point cloud scan of a target scene is created using LIDAR, RGBD sensors or structure-from-motion
- Local geometry, appearance and surrounding context is utilized to attach category labels to 3D points

WHAT WILL IT ACCOMPLISH?

- Automate a big chunk of the data annotation process currently in place to obtain desired attributes
- Provide a framework to unify existing rule-based algorithms or knowledge bases with more state-of-the-art deep learning methods
- Opens up possibilities for semantically-informed target search, navigation planning or combat training

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Work for this effort is performed by [your company/university/lab] under ONR Grant # N00014-17-1-2949.

Rich semantic attributions in large scene models, when available, greatly enhance situational awareness of warfighters as well as their capabilities for surveillance and mission planning. They can be used to manually inspect and analyze a scene in detail or to navigate through it and interact with it in an augmented/mixed reality training setup.

The objective of this program is to utilize the geometry, texture and context of outdoor scenes to compute such semantic attributions in a fully automated fashion. Aside from providing semantic information directly useful for a warfighter, the fully automated nature of this process greatly reduces the need for cumbersome manual annotations. State-of-the-art deep network architectures will be used together with domain knowledge and handcrafted rules in a hybrid system where available rules constrain the training process of the neural networks that fill in additional information implicit in annotated data. This novel framework that unifies rule-based algorithms with neural networks is capable of providing very accurate segmentation results, especially when large amount of annotated data is not available, which is often the case with 3D data.

The resulting high-quality semantic attributions open up further possibilities to efficiently search for and locate targets or plan navigation trajectories using these rich semantics and contextual information explicitly contained within our novel, graph-based representation. Through its data-driven ability to reason about context, our system will allow a warfighter to work effectively with partial or incomplete data.

The system is currently able to efficiently represent the contextual information present in a scene and use it to segment different object, part and terrain categories in a point cloud data. We also have a working proof-of-concept for a framework that unifies logical rules with deep networks. Next milestone is to extend this proof-of-concept to contain a set of rules regarding outdoor scenes that would be most useful for teaching the neural networks to avoid making some common-sense mistakes.

RESEARCH CHALLENGES AND OPPORTUNITIES:

- A pipeline that can deal with full, complex scenes, which is significantly more challenging than individual objects
- Computational bottlenecks: Increased dimensionality of 3D data puts additional strain on computational demands of deep neural networks and obtaining sufficiently high-resolution 3D results requires innovative network designs.
- Designing a novel hybrid system that effectively mix a neural network with domain knowledge and handcrafted rules
- Effective joint processing of 3D models and associated imagery with poses for increased reliability

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Figure 45. Layered Semantic 3D Modeling of Indoor and Outdoor Environments Data Sheet. Source: [76].

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