This is my robot. There are many like it, but this one is mine.

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ABSTRACT

The USMC is committed to developing autonomous systems that will support Marines. However, autonomous systems are only effective when users trust their capabilities enough to employ them. As machines transition from being teleoperated towards partially or fully autonomous, the performance and reasoning behaviors of the machines will further bewilder users and inhibit trust. Experience and familiarity with automation can develop trust, but the complexities, maintenance, and cost of future machines create an environment that prohibits daily real-world training with autonomous ground vehicles (AGV). These two factors contribute to an atmosphere of mistrust in valuable systems – systems designed to enhance combat effectiveness.

This research sought to understand the interactions between serious gaming and autonomous behavior development on trust. It was field-tested in a dual task paradigm with 40 participants in a 2-group design. Measurement in choice, indicators of trust, and secondary task performance (STP) were used to assess the amount of trust and preference for autonomous teammates for an Infantry Marine. The control group used a serious game to learn the capabilities and limitations of an off-the-shelf AGV. The experimental group used a serious game to "train" the autonomous behaviors of their tailorable AGV through an interactive Machine Learning (iML) approach. Time invested in the training environment was significantly greater for the experimental group. During the dual-task paradigm, there were no clear indicators of a difference in trust or STP between groups. A trend appears to be developing between time invested and choice of a trainable AGV that may imply that users would prefer a user-trained vice off-the-shelf AGV. All data collected petitions for follow-on research on the topic of serious gaming to enable an iML approach for increased trust. This research directly supports the Commandant's vision and US Army's desires to increase the use of unmanned systems in operations.

ABOUT THE AUTHORS

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INTRODUCTION

Background

As computing capabilities and technology continue to improve, there is a greater call from the Department of Defense (DoD) to deliver artificial intelligence (AI) to the services. Goals of increasing the speed of decision making and reducing risk to forces (Department of Defense, 2018a) further the demand for AI in the military's day-to-day operations. The United States Marine Corps future concepts seek to use AI to gain an edge on the battlefield. In the *38th Commandant of Marine Corps'* (CMC) *Planning Guidance* (CPG), the CMC is focused on divesting from current programs and forces to "accelerate funding and modernization of the future force" (Berger, 2019a, p. 23). In an online forum, the CMC published further guidance stating the USMC is underinvested in the use of lethal and non-lethal unmanned systems (Berger, 2019b). The result of this guidance is the *USMC 2030 Force Design* which calls for a redesign of the Marine Corps' Infantry Battalions and an analysis on the manned-unmanned capability balance (Berger, 2020).

Though the *2018 Science and Technology Strategic Guidance* from the Marine Corps Warfighting Laboratory (MCWL) pre-dates the 38th CPG, it is still prescient of the direction of movement for unmanned systems for Infantry Marines. It states, "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" (2016, p. 38). The USMC is well on their way as forms of supervised autonomy have already been field tested (Harkins, 2019), but continued improvement is still required. What follows is distilled from research work conducted by the primary author for his master's thesis at the Naval Postgraduate School in 2020.

Manned-Unmanned Teaming

The next step for the USMC and other services is to develop autonomous systems for use as teammates within manned-unmanned teams (MUM-T). The guidance for all services is outlined within the Secretary of Defense's *Unmanned Systems Integrated Robot Roadmap* from 2018. The DoD Roadmap utilizes the U.S. Army *Robotic and Autonomous Systems Strategy*'s definition for MUM-T. "[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" (2017, p. 24). Seminal work in the field of MUM-T comes from research in 1951 on Air-Navigation from Fitts et al. Fitts et al. created the baseline concept of humans are better at – machines are better at (HABA-MABA) (1951).

The DoD roadmap acknowledges that a lack of trust within the man-robot team is a future challenge (Department of Defense, 2018b). Compounding issues that will influence trust within MUM-T are the black-box nature of AI, live training opportunities, and system costs. A system or process that allows for the human to train with the robot to develop autonomous behaviors in a serious gaming environment could mitigate the compounding issues to positively influence trust within the MUM-T.

To achieve synergy within MUM-T, Johnson et al. advocate for a co-active design process for analyzing the HABA-MABA sub-tasks to the team's task (2011). In 2014, Johnson et al. defined the interactions between the teammates (both human and unmanned) with the three following terms: "Observability—making pertinent aspects of one's status, as well as one's knowledge of the team, task, and environment observable to others; Predictability—one's actions should be predictable enough that others can reasonably rely on them when considering their own actions; Directability—one's ability to direct the behavior of others and complementarily be directed by others" (Johnson et al., 2014). From these terms, predictability ties directly to trust through reliability.

Trust within MUM-T

A critical element in any relationship is trust. In 2004, Lee and See's research *Trust in Automation: Designing for Appropriate Reliance* defines trust as "the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability" (2004, p. 54). Reliance and trust are linked through the idea of attitudes and behaviors. Lee and See concisely state the concepts developed by Ajzen and Fishbein in 1980 and Fishbein and Azjen in 1975 that "trust is an attitude, reliance is a behavior" (2004, p. 53) and that attitudes develop behaviors (2004). Lee and See model trust as a feedback loop that refines itself over iterations of a user's observations of performance. Building from Lee and See (2004), Sheridan (2019) solidifies the concept of trust as a mental model and utilizes a Kalman control system feedback loop (1960) to show its evolution (Figure 1). The same publication indicates the ability for the human's mental model to predict the observed actions of the unmanned teammate confirms trust. If expectations do not match the observed behaviors then the mental model is updated (2019). The greater the time steps between the human's attempt to observe the teammates actions can indicate a higher degree of trust. The ability of the human's mental model to predict the robot's actions requires an intimate understanding of the robot's behaviors. The human will require familiarity of the inputs the robot receives to create outputs, as shown by the curvy box in Figure 1.

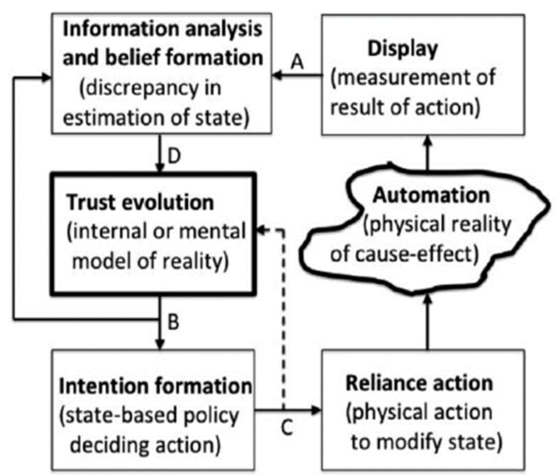

Figure 1. Sheridan's Control Model of Trust. Source: (Sheridan, 2019).

Agent Development

Agent to Automation, Autonomy, and AI

Henceforth, *robot* will refer to hardware of the unmanned teammate, while the agent is the software that controls the robot. The agent is a synthesis of automation, autonomy, and AI. The DoD Roadmap and AI Strategy define clear and usable terms. Defined in increasing complexity: "[Automated systems] are governed by prescriptive rules that allow for no deviations" (Department of Defense, 2018b, p. 17). "Autonomous systems are governed by broad rules that allow the system to deviate from the baseline" (Department of Defense, 2018b, p. 17). AI is "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" (Department of Defense, 2018a, p. 5). Robot actions will be created and controlled by an agent that can execute simplistic tasks, understand intent, and learn.

The development of the agent's behaviors can range from a programmer's coding to machine learning (ML) techniques. Gunning and Aha of the Defense Advanced Research Projects Agency (DARPA) Explainable AI (XAI) program generalized an agent's performance and explainability as: when performance increases, explainability decreases (2019). The lowest performance with greatest explainability is a programmer's hard coding of rules. The greatest performance with the lowest explainability is a deep neural network's development of rules. Even with easy explainability, the developed agent's behaviors may not be the desired actions of the human teammate. Additionally, to achieve the full advances of ML and AI within MUM-T lesser XAI is required for use. A process that allows users to develop trust is required. A necessary step to attain calibrated trust is for the human teammate to build their mental model as the agent's behaviors mature.

Interactive Machine Learning and Trust

The current approach to traditional ML – automatic ML (aML) – is for a ML expert to develop the agent through the adjustment of parameters and algorithms based on the end-user's data and insights (Amershi et al., 2014). In 2014

Amershi et al. published *Power to the People: The Role of Humans in Interactive Machine Learning* (iML), they show how iML can be used to tighten the coupling between user and agent. Amershi et al. advocate that iML is the end-user's involvement in the rapid, focused, and incremental development of the agent's behaviors (2014). One of the three DARPA XAI performers focused on autonomy is using a form of iML for developing a more explainable AI. That performer, the Palo Alto Research Center, created a virtual environment for the development of agent behaviors and MUM-T concepts titled the COmmon Ground Learning and Explanation (COGLE) project (Stefik, 2018). Within their virtual environment, the end-user and agent take a teacher-to-student form to execute a curriculum of instruction to develop agent behaviors and enable ML processes (Stefik, 2018). The process aims to develop a common ground for both the agent and end-user (Stefik, 2018). The development of the common ground can refine the human's mental model of the agent.

Gutzwiller and Reeder's most recent publication of trust and iML provided evidence that users may trust iML developed agents more (2020). In their research, multiple agents were developed and shown to the end-user during the ML evolutionary process. In an iterative fashion, the end-user would assess multiple agents and select one for further development in the ML environment. This process was repeated for a set number of iterations. They concluded, "The IML [interactive machine learning] 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)" (2020, p. 3). Though Gutzwiller and Reeder were able to show that end-users trusted iML developed agents more, they did not explore if that trust would transfer to execution with a live robot.

Virtual Environments and Serious Gaming

The interactive approach used by the robotics community for development of robotic behaviors can be categorized as automatic programming (Biggs & MacDonald, 2003). In Biggs and MacDonald's *A Survey of Robot Programming Systems*, automatic programming allows for the robot to generate code from a variety of indirect ways. The actions can be demonstrated or directed by a user in either live or simulated virtual environments (2003). This approach can be applied in agent development of autonomous robots.

Simulations and virtual environments are heavily embedded into the DoD services for developmental testing, wargaming, and training. The Marine Corps utilizes virtual environments and simulations for individual, small-unit, and staff training (Telford, 2016). Of the many benefits of training, two critical outcomes are: mission familiarity and the practice of battle drills (Headquarters Marine Corps, 1997).

EXPERIMENTATON

The DoD and USMC guiding concepts and the literature review drove us towards the exploration of trust within MUM-T, specifically with squad leaders within the Marine Corps Infantry Community. With the DoD's use of simulations and serious gaming for training, an approach that incorporated an agent's development of autonomous behaviors within serious gaming was used. Measuring the transfer of trust of the agent in a simulated environment to an autonomous robot's execution of a task was planned to provide insights into the demographic's cultural perspective towards technology, acceptance of autonomous systems, and best approach for autonomous behavior development. The proposed hypotheses of the research were:

H1: There will be a greater proportion of Marines who will choose to use the "autonomous" robot over "tele-operated" 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. ($\mu_{iML} - \mu_{aML} > 0$).

Methodology

Design

We crafted an experiment to measure a human's transfer of trust from a simulated to live environment for an unmanned autonomous teammate. Additionally, a survey of the current force was conducted to identify the type of control they would want in their unmanned teammate. The study was a "two-group dual-task paradigm designed to measure choice, trust indicators, and [STP]" (2020, p. v). The control group, Group B-aML, conducted serious gaming to learn the capabilities and limitations of an aML "off-the-shelf" robot while the experimental group, Group A-iML, trained the agent's behaviors for the robot.

Participants

There were 40 Infantry Marine participants with ranks ranging from Lance Corporal to Sergeant. As there is limited experience across the combat arms military occupational specialties (MOSs) in MUM-T operations, we provided a succinct foundation for the participants to understand the research domain and experimental environment. Although we hosted the Marine Corps' squad leaders on a Military Operations on Urban Terrain (MOUT) range, they were still leaving their primary training to take part in this experiment. The Marines we hosted were from the Advanced Infantry Training Battalion (AITB) East's Advanced Infantry Marine Course on Camp LeJeune, NC. Weather impacts in Camp Lejeune during the research week caused the experiment to shut down early, leaving us with a substandard sample size.

Materials

In our setup for the conduct of the experiment, we maintained a tactical immersion for the participants. The setup (Figure 2) contained two Alienware M51 Laptop Computers, one GoPro Video Camera, one set of Tobii Pro Glasses, one portable computer screen, one Microsoft X-Box controller, and two program of record "small, unmanned ground vehicles (SUGV)". Our live tactical scenario environment included one cardboard box required for inspection in the tactical area, and two buildings: one to house the experiment and the other to be used as the objective building for room clearing. Adjacent to the two buildings was the tactical assault position. The Marine participating had to decide when he would send a Fire Team from this position to continue towards their objective as part of the experiment.

Figure 2. Participant's Workstation. Source: (Yurkovich, 2020).

Procedures

To start, participants completed a baseline assessment with an attention enumeration task (AET), a timed task for counting and entering the number of blocks seen on the screen. Once the AET was completed, the participant then played the serious game by controlling the SUGV avatar. The games differed based on the group assignment. Group A-iML used the serious game to "train" the agent through a set number of repetitions of basic tasks. Figure 3 shows a screenshot of the Group A-iML game. Participants in Group B-aML were learning the robot's capabilities in the simulated environment. Both groups played the game and were given the opportunity to decide whether they would want to teleoperate or use their form of autonomous behaviors (iML vs. aML) for the robot to perform the reconnaissance and room clearing task. If they chose to teleoperate the robot, we artificially intervened by telling them that we were having issues with the remote control. This was one of three areas of deception required to execute this experiment.

For the iML participant (Group A), we incorporated a second form of deception. When the Marine played the serious game, a researcher was studying and tracking his tendencies and trends within the game. This allowed for that same researcher to manually operate the robot from behind the scenes during the execution of the live task. Although the robot was not autonomous and controlled in a Wizard of Oz (WOZ) like manner, we wanted to give the impression of autonomy and machine learning by mimicking the behaviors the participant displayed during game play. The final form of deception was when a researcher would load the serious game data into the SUGV to drive its behaviors in the courtyard and in the building. The researcher used a batch file showing a false download of the data to simulate retrieval and upload to the SUGV.

The aML participant (Group B) was also given the opportunity to select teleoperated or autonomous, but again the teleoperated option was not possible. Instead, the participant was told that the SUGV was "off-the-shelf" and controlled by code developed by a leading technology firm in Silicon Valley.

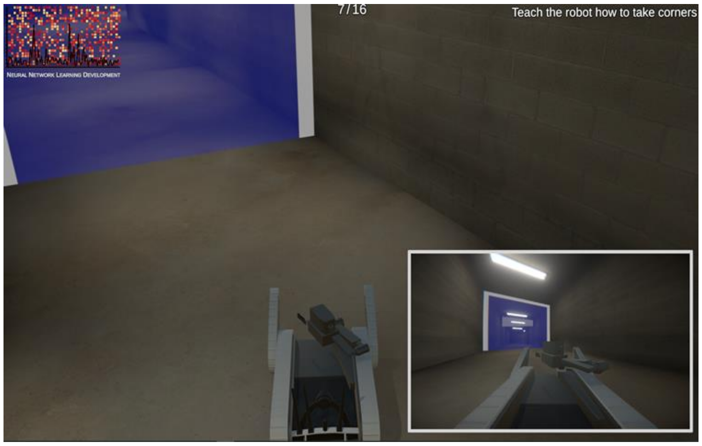

Figure 3. iML Serious Game. Source: (Yurkovich, 2020).

The WOZ would still control the robot for Group B-aML, but in this instance, the WOZ followed the same script for every participant in this group and did not try to mimic behaviors displayed within the serious game.

During the actual reconnaissance and room clearing task, the participant was required to complete a second AET which served to replicate the secondary tasks a squad leader would execute during MOUT operations, such as cross boundary coordination and coordination of supporting arms. We anticipated the participants would spend most of their time completing the task rather than looking at the screen showing the robot's camera view. However, we made the camera available to the participant to check progress in the reconnaissance and clearing task and measured the number and duration of "looks" at this screen to serve as indicators of trust.

Upon completion of the AET, live data collection ceased. Participants were then asked if they would send their subordinate fire team across the courtyard and into the objective building, regardless of the status of the SUGV. Once affirmation was received, the experiment ended, and the participant transitioned to completing the trust survey.

Data Analysis

Data compiling was completed for the AETs on the *Presentation* program while the eye tracking data utilized the *Tobii Pro Lab*'s Area of Interests functionality. The data was sorted via *python* code for analysis in *JMP*. For the comparison of choice, directly associated with H1, a one-sided Two-Proportions z-Test ($\alpha = 0.05$) was planned for use, but was replaced by Fisher's Exact Test due to not meeting the assumption requirement of 10 success and failures per option. For H2, a mix of multivariate analysis of variance (MANOVA) and a Two-Sample t-Test were planned for, but the t-Test was replaced by the Wilcoxon Signed-Ranks Test ($\alpha = 0.05$) due to non-parametric data. Within the data for the AETs, the Robust Fit Test for Outliers with 2.5 standard deviations were used to identify outliers who failed to follow the directions for the AET. For data recorded with the Tobii Pro Glasses, data was excluded for either degraded eye-tracking or looking exclusively at only the SUGV screen or AET during live execution as the data recorded as null for the comparison.

Results

Hypothesis 1 – Choice
A Fisher's Exact Test revealed there was "no significant difference in the proportion of Marines choosing to use the autonomous mode in iML (Group A) rather than the aML (Group B) approach with 63.1% (12/19) choosing autonomous mode for iML, compared to 42.9% (9/21) for aML ($p = .167$)" (Yurkovich, 2020, p. 75). A graphical comparison is shown in Figure 4.

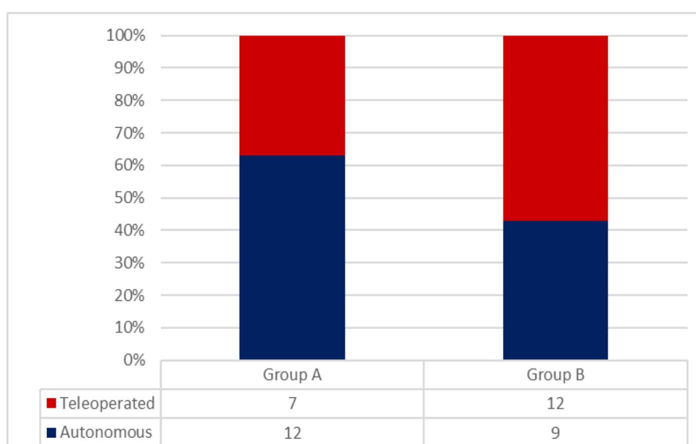

Figure 4. Choice Comparison. Modified from: (Yurkovich, 2020).

Hypothesis 2 – Trust
All data recorded for indicators of trust and secondary task performance fail to reject the null hypothesis. A limitation to the data was the smaller than expected number of participants which prevented statistical significance on

multiple tests. Six behavioral aspects were measured while the attitude of trust was measured post execution with a randomized trust in automated systems survey (Gutzwiller et al., 2019; Jian et al., 2000).

"Difference in Overall Time of Task" is a STP measurement as the difference in time to complete the baseline AET as compared to during the dual task condition where participants completed another AET while the SUGV executed its task. A number closer to zero is desired. "Glances at Robot" is a count for the number of times that a user looked at the SUGV during the dual task. In connection with Sheridan's 2019 research, fewer glances would indicate greater trust. For the "Trust in Automated Systems" survey results, the negatively biased questions were inverted to match the positively biased questions. A number closer to seven is desired. Table 1 shows the consolidated statistics for the two sample test results.

"Average 'Look' Time Duration" is the averaged time for each look at AET and SUGV screen. Longer duration on the AET and lower on the SUGV screen is the desired outcome. Two different reactions times were recorded for each execution of the task: 1) as the AET recorded time to count the blocks (Initial Reaction Time) and 2) the time to enter the number (Input Reaction Time). An outcome closer to zero was desired. Figure 5 shows the relationship of average look durations. Figure 6 shows the relationship of reaction times between the groups. Table 2 shows the consolidated statistics for the MANOVA test results.

Table 1. Two Sample Test Results.

Data Comparison	**Recording Input**	**Test**	**Results**		
			Group A (iML)	Group B (aML)	Comparison
Difference in Overall Time of Task	*Presentation*	Wilcoxon Signed-Ranks Test	*M* = -92,876 *SD* = 123,331	*M* = -54,434 *SD* = 77,451	*Z* = -0.717, *p* = .47, *d* = 0.373
Glances at Robot	*Tobii Pro Eye Tracking*	Wilcoxon Signed-Ranks Test	*M* = 37.18 *SD* = 36.80	*M* = 36.61 *SD* = 27.34	*Z* = -0.215, *p* = .82, *d* = 0.018
Trust in Automated Systems	*Survey*	Two-Sample t-Test	*M* = 4.79 *SD* = 0.181	*M* = 4.96 *SD* = 0.172	*t*(38) = 0.669, *p* = .75, *d* = 0.211

Table 2. MANOVA Test Results.

Data Comparison	Recording Input	Test	Results
Average "Look" Time Duration	*Tobii Pro Eye Tracking*	MANOVA	$F(1,25) = 0.804$, $p = .459$, $\eta_p^2 = .060$
Difference in Average Reaction Times	*Presentation*	MANOVA	$F(1,31) = 0.656$, $p = .526$, $\eta_p^2 = .041$

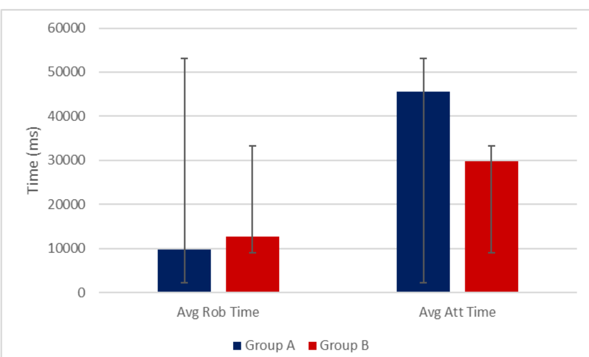

Figure 5. Average "Look" Time Comparison. Modified from: (Yurkovich, 2020).

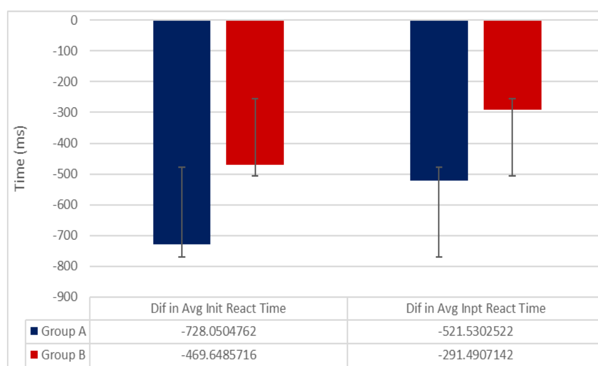

Figure 6. Reaction Time Comparison. Modified from: (Yurkovich, 2020).

While the performance in the secondary task in the AET data tends toward greater trust in the SUGV for aML Group (B), the amount of time invested in "looks" does not. All data is inconclusive in identifying a significant difference in performance and behaviors to indicate a greater amount of trust between groups.

A significant difference was found between groups for time invested in the serious game to complete the exact same tasks. In the serious game, Group A (iML) "trained" the SUGVs behaviors for autonomous execution while learning its capabilities and limitations by controlling the SUGV's avatar; Group B (aML) strictly controlled the avatar to learn capabilities and limitations. A one direction Two-Sample t-Test indicates "times were higher for iML – Group A ($M = 1150$, $SD = 94.7$) than for aML – Group B ($M = 898$, $SD = 70.6$), $t(15.55) = -2.05$, $p < .029$, $d = 3.017$" (Yurkovich, 2020, p. 83).

DISCUSSION

Recommendations

Unmanned Teammates

The unmanned teammate should arrive to the unit in the same fashion as a newly minted graduate of the School of Infantry arrives at an infantry battalion. The Marine possesses a baseline of techniques and procedures and is prepared to join a fire team. The agent will be programmed with a baseline set of autonomous actions like obstacle avoidance, threat detection, and an understanding of basic infantry techniques and procedures.

Elements that deliver the application of the techniques and procedures will be developed by the human. In 2019, Marine Corps Captains Franco and Spada utilized Johnson et al.'s (2014) interdependence analysis framework to develop the responsibilities of a MUM-T for occupying a support by fire position. Non-lethal decisions that were left to the unmanned teammate were: position in formation, appropriate speed, and to avoid or proceed near an obstacle (Franco & Spada, 2019). These decisions are situationally dependent and a simple response to this concern is for the human to control these parameters, but then the human is quickly relegated to a "controller," thus defeating the aim of MUM-T. As a young Infantry Marine would learn through training scenarios, so should the unmanned teammate's agent.

Through a training curriculum, the agent's baseline tasks will be improved through training in a virtual serious game environment with an iML approach. To maintain adaptability, the agent must be able to record its state and action spaces during live events to allow for a voice initiated after-action review. While learning and adapting is a critical element for success on the battlefield (Headquarters Marine Corps, 1997), this AI enabled trait should only happen with the approval of the human. Authorization would occur during tactical pauses or rest and refit operations after the agent demonstrates the new behaviors in a virtual environment.

Use of Serious Gaming for iML

The serious game developed for iML training should have three training modes. The first will be for the human to control the robot to learn the physical capabilities and limitations of the system. The second form is scenario-based virtual training where a human will control the human's avatar, and an additional human will control the robot's avatar. These scenario-based training events will serve as the example for supervised ML to replicate. The third form is when both teammates fulfill their respective roles in the virtual environment. Within this mode, the human will have the ability to provide positive or negative rewards to the agent to continue to refine its behaviors. Additionally, the agent can develop expectations of the human during these iterations.

While the human is not executing virtual training with the unmanned teammate's agent, the agent will continue to execute ML algorithms to develop a better agent. When the human logs in, the human will be presented with demonstrations of multiple ML evolutionary agents that were produced. The human will then choose which agent to continue to develop, discarding the rest.

A benefit of the curriculum style approach is that it keeps the human informed of the training the agent completed. This will prevent misuse and disuse cases in live execution. Additionally, it will allow for the trust and "IKEA" effect that Gutzwiller and Reeder stated (Gutzwiller & Reeder, 2020), as shown by the significant difference in the amount of serious gaming time.

Implementation into a Marine Corps Infantry Battalion

The limitations of training time and areas and fiscal considerations are the catalyst for developing the concept of how unmanned teammates will be implemented into a Marine Corps Infantry Battalion (Yurkovich, 2020). Figure 7 shows the lifecycle of the unmanned teammate in day-to-day training and operations. Beginning in the top-left, the team trains in the serious game as outlined above. The agent is exported for use and brought to the RoboPool via the Transfer Agent Device (TAD). The RoboPool is similar to the motor-pool and armory each infantry battalion maintains. The robot is maintained and updated at this location. In the top right of the figure, the team deploys to field for its live operations, either training or in support of the greater DoD mission. The team operates with calibrated trust as the team has a shared understanding and mental model of each teammate's capabilities and limitations. After the live operation, the human provides a verbal after-action to the agent through a negative or positive reward comment. As intelligence / operation cycle continues to develop the follow-on mission, an unmanned aerial vehicle is launched to capture data to develop an intelligence picture and adversarial actions. In the bottom left, the S-2 – Intelligence Section compiles the environment and inserts adversarial agents to develop a serious game for the MUM-T to use for a rehearsal prior to execution. If time permits, ML algorithms compile updated behaviors for the agent. Once the operations are complete, the robot is returned to the RoboPool and the TAD is brought along with the human for continued training.

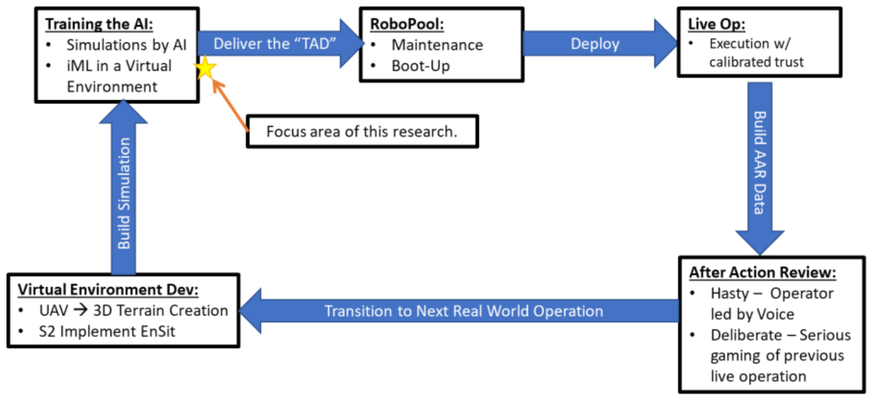

Figure 7. Conceptual Model for Implementation into an Infantry Battalion. Source: (Yurkovich, 2020).

Operational Testing

Testing with Marines from the Fleet Marine Force (FMF) created an environment of shared learning between researchers and the Marine Corps' future squad leaders. To researchers, it reinforced the true purpose of the research—providing the Marines at the tactical edge with the best we can conceive. It showed the Infantry Marines that there are people genuinely interested in improving their advantage against our future adversaries.

Future Work

Experimental Redesign

A follow-on experiment to this research should remove the option for choice between teleoperated vs. autonomous mode, place the participant in an environment with increased vulnerability, and include an autonomous agent playback portion.

During the experiment, participants were provided the opportunity to choose if they would like to use the SUGV in teleoperated or fully autonomous mode to satisfy a hypothesis aimed at identifying the preference of current Infantry Marines. A comparison of choice to trust survey results in a Two Sample t-Test did not reveal a significant difference, ["autonomous" mode ($M = 5.04$, $SD = 0.168$) to choosing "remote control mode" ($M = 4.69$, $SD = 0.177$), $t(38) = -1.47$, $p = .150$, $d = 0.373$]; but the difference may indicate a bias. We believe this possible trend exists for one of two reasons: 1. As the remote control for teleoperated mode was "broken," this may have degraded the trust in the system. 2. The participant's trust was pre-established at a lower level and remained there for the duration of the execution. The lower level of trust may have driven the participant to choose the teleoperated mode. A pre-experiment trust survey could possibly unearth the reasoning at the expense of biasing the participants as to the intent of the research. We recommend moving the choice to a survey question following execution with the autonomous mode.

Lee and See establish that trust is dependent upon a situation's "uncertainty and vulnerability" (2004, p. 54). During our research, the participant created their own atmosphere of risk and uncertainty. We relied on the participant's motivation to do their best during the dual task paradigm. Including a competition and an atmosphere for positive and negative rewards to the user in the next iteration of this research could improve the user's requirement for trust.

While the research team identified the need for a playback portion of the autonomous agent's behaviors upon completion of the serious game, resource constraints prevented the implementation. If a WOZ approach is used, multiple pre-recordings reflecting the different preferences of the participant's trained behaviors could be pre-loaded for remote selection by the WOZ for playback. Ideally, future iterations of this research can develop an autonomous agent.

Autonomous Agent Development

A byproduct of this research was to gauge if the efforts to create an autonomous agent via an iML approach within a virtual environment to transfer to a real robot was a worthy endeavor. It is expected to be a challenging future step. There are ML developed autonomous agents that have made the jump from simulation to real world (Wiggers, 2019), but the literature does not reveal any from an iML approach.

A possible way to test with a similar demographic and begin to create a baseline dataset would be through a web-based gaming application. Participants could remotely log-in to execute the curriculum. As a demonstration of the agent's performance is required for approval and a calibration of trust, a positive or negative reward for learning should also be incorporated. The U.S. Army's Early Synthetic Prototyping environment, *Operation Overmatch*, aligns with this concept of web-based testing, recording, and evaluation and could serve as a future sandbox.

Serious Gaming Environment Development

Significant coupling between machine vision and modeling experts is required to create a serious gaming environment. Robotic experts acknowledge that simulations are valid for preventing wear on systems, but lack the fidelity to replicate the noise within the real world (Bingham, 2019). The serious gaming environment for the iML approach would require the appropriate object classifications within both the simulated environment to match the machine vision algorithms. Priority should be given to the objects that are part of the agent's state of inputs and outputs, e.g. doorway and obstacle identification.

CONCLUSION

Motivated by bringing the best resources to our warfighters, this research aimed to understand the development of trust within a MUM-T and how it transfers from a virtual environment to real life based on differing approaches for autonomous behavior development (Yurkovich, 2020). Though many of the results were not significantly significant due to the limited number of participants, we did find that the iML approach group invested more time in the serious gaming environment where they "trained" the agents behaviors while the counterparts strictly learned about the agent. This, in coordination with the non-significant trend in choice, creates an indication that Infantry Marines may prefer to use an autonomous teammate development through an iML approach. There were no indications or trends on trust. Future research is needed for the continued exploration of the topic for the use of serious games and the iML approach. Those studies can then inform decisions and actions on how to best develop greater trust and efficiency with MUM-T through aligned mental models and expectations of performance.

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