ABSTRACT

YAGODA, ROSEMARIE ELAINE. You Want Me to Use THAT Robot? Identifying Underlying Factors Affecting Robot Use. (Under the direction of Dr. Douglas Gillan).

Building on traditional technology acceptance and human-robot interaction (HRI) research, this research sought to investigate operational HRI factors affecting robot use within the context of a high-risk environment. Technology acceptance models have previously focused on perceived usefulness and ease of use, but have tended to ignore barriers or external factors associated with technology adoption. The present studies investigate the role of barriers such as operational risk and lack of HRI trust in determining acceptance of robots. Experiment 1 empirically refined the experimental methodology used in Experiment 2 to investigate factors affecting robot use. Overall, the results highlighted the influence of HRI trust and operational risk on the likelihood of robot use; in addition, they shed light on the importance of the configuration of the robot capabilities needed for task completion. With the proposition that these relationships were moderated by the robot configuration, HRI trust was shown to increase the overall likelihood of robot use and only slight variations were attributed to increased operational risk. HRI trust was shown to have both a positive and negative influence in terms of the operational risks associated with on robot use. In fact, instances when HRI trust is high may lead to using a robot that is not even properly configured for the high-risk task. Therefore, it is beneficial to understand the underlying mechanisms that influence the perception (right or wrong) surrounding unmanned systems. The findings from this research can be used to enhance the utility and acceptance of new or existing unmanned systems.

You Want Me to Use THAT Robot? Identifying Underlying Factors Affecting Robot Use

by
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BIOGRAPHY

Rosemarie E. Yagoda completed her undergraduate studies in May of 2008 at the University of South Florida in Tampa, Florida. She attained a Bachelor of Science degree in Psychology with University and Departmental Honors. After graduation she moved to Raleigh, North Carolina, where she began her graduate studies within the Psychology Department at North Carolina State University in the Fall of 2008. There she earned her M.S in Human Factors and Ergonomics Program in 2011 and her Ph.D. in the same discipline in 2013 while working as a Scientist, specializing in Human-Robot Interaction, for the U.S. Navy.

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INTRODUCTION

> "At the time I was supporting a Route Clearance Platoon in Baquba, Iraq. IEDs were located at almost every intersection. Some had been buried for months, and the ground was as hard packed as if concrete. A request for EOD support came in for a possible IED located inside of a house where personnel had already been walking around inside. I was located nearby and could see the house from my location. After clearing 3 IEDs nearby I drove to the location and spoke with the platoon leader. He gave me a location of the possible IED. I entered the building. The ground was littered with garbage and broken cinder blocks. I identified a suspicious pile underneath the stairwell. There were 2 pipe bombs connected with red detonating cord. I performed a quick 360-degree survey of the area. Just as I turned to walk out of the stairwell, the IED detonated." – *SCPO Timothy "Timmy" Johns, USN*

Over the past decade unmanned systems have proven to have a significant impact on warfare worldwide. Unmanned systems have afforded the warfighter the capability to conduct high-risk operations at a distance; which clearly reduces the risk to human life during combat operations. While the benefits are substantial, there have been many obstacles to general operational acceptance of unmanned systems within military applications (Defense Science Board, 2012).

Due to the demands of conflict and urgent combat needs, unmanned systems have been rapidly deployed while still in a developmental capacity which has created many operational challenges. Since the primary focus has been mainly on autonomous platform and sensor research, development and deployment (R&DD), only little attention was paid to the actual "human-in-the-loop." As a result, the concept of operations (CONOPS) and corresponding training were immature, leaving the "human-in-the-loop" unprepared and unable to appropriately use the unmanned systems provided to them (Defense Science Board, 2012). Such a technology-centered R&DD emphasis on the design of autonomous capabilities, rather than on the operational needs and performance expectations, has created difficult human-robot interaction (HRI) challenges with respect to situational awareness (SA), perception and performance, and workload (McDermott, Gillan, Riley, & Allender, 2009). Unfortunately, these challenges have resulted in many unmanned systems that have been deployed, but never fully adopted. In order to gain a better understanding of this lack of adoption, the underlying mechanisms behind the initial acceptance of new technology needed is first explored.

Several acceptance models, differing in content and complexity, have been developed based on theories used to predict behavioral intent leading up to technology adoption. Both the theory of reasoned action (TRA; Fishbein & Ajzen, 1975) and the theory of planned behavior (TPB; Schifter & Ajzen, 1985) have been used to understand, explain, and model predictive variables that contribute to technology acceptance (Venkatesh, Morris, Davis, & Davis, 2003). The TRA states that attitudes toward a behavior influence behavioral intent;

whereas TPB expands the TRA by adding an additional construct of perceived behavioral control as a determinant of behavioral intent (Ajzen & Madden, 1986).

Building upon TRA, the Technology Acceptance Model (TAM) was next proposed to further explain underlying behavioral intentions (Davis, Bagozzi, & Warshaw, 1989; Davis, 1989). Multiple extensions of the TAM have been developed based on two core constructs: perceived usefulness (PU) and perceived ease of use (PEU; Venkatesh & Bala, 2008; Venkatesh & Davis, 2000; Venkatesh et al., 2003). PU is the extent to which a person believes that using the system will enhance their job performance; whereas, PEU is the extent to which a person believes that using a system will be free of effort (Venkatesh & Davis, 2000). TAM and its derivatives are the most widely used models to understand *why* people use technology (King & He, 2006). Overall, the core constructs have demonstrated high reliability and validity towards assessing user acceptance in a variety of domains (Chin, Johnson, & Schwarz, 2008).

TAM2 (Venkatesh & Davis, 2000) incorporates additional theoretical constructs ranging from social influence processes (subjective norm, voluntariness, and image) to cognitive instrumental processes (job relevance, output quality, result demonstrability, and perceived ease of use). Overall, TAM2 has been shown having a 17% prediction accuracy of technology acceptance (Venkatesh et al., 2003). Legris, Ingham, & Collerette (2003) conducted a meta-analysis revealing that both the original TAM and TAM2 are useful models; however, both only account for at best 40% of the variance associated with predicting technology use. In response to the relative lack of fidelity in TAM2, the Unified

Theory of Acceptance and Use of Technology Model (UTAUT) was developed by Venkatesh, Morris, Davis, & Davis (2003). UTAUT has condensed the 32 variables into four main effects and four moderating factors yet only resulted in an effective use prediction rate of 42%. Following, TAM3 was developed based on TAM2 and theorized determinates of PEU (Venkatesh & Bala, 2008). The purpose of this integrated model was to predict and enhance the potential adoption and use of technology at an individual level based on experience. Yet, TAM3 resulted in an effective use prediction rate of 7% lower than UTAUT, comparatively speaking.

A recognized limitation of the original TAM is that it does not account for any barriers or external factors associated with technology adoption (Pijpers, Bemelmans, Heemstra, & Van Montfort, 2001; Straub & Limayem, 1995; Taylor & Todd, 1995). As such, research has sought to extend the TAM by incorporating external variables to explain the additional variance in use intentions. Some of these extensions are particularly complementary to HRI research regarding initial unmanned system acceptance and adoption. In fact, unmanned systems not properly designed to meet the operational needs and performance expectations of the mission will not be adopted and fully utilized for their intended benefit during dangerous operations (Defense Science Board, 2012).

Failure to acknowledge operational HRI requirements within the bounds of the mission, often leads to unexpected system failures due to design oversight (Roth, Bennett, & Woods, 1987). Thus, underestimating the complexity of the task or overestimating performance predictability can lead to unmanned systems not properly configured to accomplish the mission (Ghazizadeh, Lee, & Boyle, 2012). When an unmanned system is not properly configured, the core technology acceptance constructs (i.e., PEU and PU), that have demonstrated high reliability and validity, have essentially been disregarded. In turn, these design failures lead to ineffective human-robot collaborations (Chen, Haas, Pillalamarri, & Jacobson, 2006). In order to enhance the initial acceptance of unmanned systems, effective HRI is needed. Thus, better HRI design configurations are needed to not only increase trust in the reliability of the system, which would improve overall mission performance, but to ultimately accelerate robot adoption.

As new unmanned systems are being released into the field, their operational adoption largely depends upon the quality of the initial human-robot collaboration. Effective HRI assures that the design of the unmanned system capabilities are functionally allocated to support safely accomplishing the mission (Yagoda, 2012),which is especially vital during combat operations (Miller et al., 2011). This omnidirectional interaction between human(s) and robot(s) implies a functional perspective of control delegation (Mantel, Hoppenot, & Colle, 2012) that inherently requires a certain level of trust (Moray, Inagaki, & Itoh, 1998). Just as trust mediates relationships between people (Rotter, 1971), people tend to use machines (Muir, 1988) and rely on automation (Ghazizadeh, Lee, & Boyle, 2012; Lee & See, 2004; Parasuraman & Riley, 1997; Sheridan & Parasuraman, 2005) they trust. In turn, trust evolves through task performance and the quality of past interactions (Gabarro, 1978), 1978); which could infer the more an operator trusts the effectiveness of the robot the higher the likelihood of use (De Visser, Parasuraman, Freedy, Freedy, & Weltman, 2007).

The evolution of HRI trust can be described based on function, performance, and semantics within five overall areas: team configuration, team process, context, task, and system (Yagoda & Gillan, 2012). Trust can affect an operator's willingness to functionally allocate tasks, disseminate information, and collaborate with the robot during the mission (Freedy, DeVisser, Weltman, & Coeyman, 2007); thus, poorly calibrated trust hinders both team performance and mission effectiveness (Chen & Barnes, 2012; Lee & See, 2004; Parasuraman, Sheridan, & Wickens, 2000).

A meta-analysis conducted by Hancock et al. (2011) concluded that robot performance-based factors were highly associated with trust such as: behavior, dependability, reliability, predictability, and level of automation. Given the dynamic unstructured nature of HRI, there is a high likelihood of encountering situations of uncertainty regarding the reliability of robot performance. In such circumstances, task performance expectancies could severely impact human-robot collaboration, and potentially lead to hazardous situations (Kaniarasu, Steinfeld, Desai, Yanco, & Lowell, 2012). Trust is especially critical in situations characterized by risk, vulnerability, uncertainty, and the need for interdependence (Adams, Bruyn, Chung-yan, & Mccann, 2004). Essentially, there needs to be a balance between moment-to-moment changes and an operator's ability to dynamically respond in various situations (Inagaki, 2003; Rouse, 1988; Scerbo, 1996). Thus, effective HRI requires a delegation of control to support timely operational decisions, which requires trust.

Building upon traditional technology acceptance and HRI research, this research seeks to investigate operational HRI factors affecting robot use within a high-risk environment. The following two experiments were designed in an iterative fashion where the content of the second experiment was derived from the results of the first. The intent was to examine the following hypotheses:

- Hypothesis 1: HRI trust will have a positive main effect on the likelihood of robot use.
- Hypothesis 2: Operational risk will have a negative main effect on the likelihood of robot use.
- Hypothesis 3: Operational risk is expected to moderate the effect that HRI trust has on the probability of robot use. Based on previous findings discussed, the effect of HRI trust was expected to be more pronounced as the operational risk increases.

When SCPO Johns was asked *why* he went into the building instead of using the robot, SCPO Johns responded: "*The robot was not utilized due to the fact that personnel had been walking in and around the area and the robot reliability was sporadic inside compounds and buildings*."

Experiment 1

The purpose of Experiment 1 was to refine the experimental methodology to be used in the Experiment 2. This experimental method was intended to achieve two objectives: (1) assess the perceived risk associated with various tasks for which robots would typically be used; (2) identify which of the thirty-six tasks for which each robot would likely be used. Experiment 1 focuses on high-risk applications in which robots are employed for conducting dangerous operations at a distance, in order to improve the likelihood of survivability. In doing so, each task was intended to be not only operationally relevant, but also to simulate real world instances in which an unmanned ground vehicle (UGV) would be used.

During this experiment, participants were to rate the *probability of mishap occurrence* and *severity of mishap effects* for thirty-six tasks associated with either EOD or ISR operations ranging from “Disable an improvised explosive device in a highly populated hostile environment” to “Remove 30lbs of small rocks off of a person.” Participants were then instructed to determine which of the thirty-six tasks each robot would likely be used for, based on a photo and respective manufacturer specifications. This resulted in six capability-based task parings unique for each robot that will be utilized to examine the hypothesized effect of HRI trust and operational risk in following experiment. It is important to note the results from this experiment are only applicable to UGVs within a simulated environment.

Method

Participants. 50 participants (Males = 29; Females = 21), between the ages of 18 and 67 (M = 34 years old), were recruited using a crowdsourcing web service, Amazon, Inc. Mechanical Turk (http://www.mturk.com). All participants resided in the United States and had an acceptance rate (i.e., successful completion of previous Human Intelligence Tasks or "HITs") greater than 95%. The average completion time for the study was 33 minutes and participants were compensated $0.80 resulting in an effective hourly rate of $1.46.

Materials and Procedure. *After signing an informed consent, thirty-six tasks (see Figure 3.* Risk assessment results for the thirty-six tasks evaluated during Experiment 1.

) were first evaluated in terms of operational risk. In doing so, participants were to assess the probability of mishap occurrence (*Frequent* to *Improbable*) and severity of the mishap effects (*Catastrophic* to *Negligible*); referencing the MIL-STD-882E (Department of Defense, 2012) definition of a *Mishap*: "An unplanned event or series of events resulting in death, injury, occupational illness, damage to or loss of equipment or property, or damage to the environment," for additional clarification and response consistency. Task presentation order was randomized for each administration.

After operational risk evaluations were completed, participants were instructed to rate the likelihood of robot use for each of the thirty-six tasks. In order to facilitate these evaluations, *Robot Profiles* were generated. Each robot profile contained a photo and the manufacturer specifications for each of the six robots (see Figure 1) evaluated.

Figure 1. Unmanned Ground Vehicles (UGVs) evaluated during Experiment 1.

The six *Robot Profiles* used during Experiment can be found in Appendix A. For each robot, participants were also asked to rate the *likelihood of use* by indicating the extent to which they agree with the following statement: *If I needed to accomplish this task, and the choice was up to me, I would use this robot*. Participants were provided a 7-point Likert scale (*Strongly Disagree* to *Strongly Agree*) to express their level of agreement. The likelihood of robot use was assessed for each of the thirty-six tasks prior to presenting the next robot. The sequence of robots and task presentation order were both randomized for each administration. The experiment concluded after all robots were evaluated.

Results

In order to assess operational risk, probability of mishap occurrence (*Frequent* to *Improbable*) and severity of the mishap effects (*Catastrophic* to *Negligible*) responses were used to classify each task within the Risk Assessment Matrix (RAM) framework. This risk classification procedure is constant with the Department of Defense Standard Practice for System Safety (MIL-STD-882E; Department of Defense, 2012). Assessed risks are expressed as a Risk Assessment Code (RAC); which is combination of one severity category and one probability level that generates a numerical classification value between *1* and *20*. This method ultimately allows an analyst to decompose risk into four general categories: *High*, *Serious*, *Medium*, *Low*. The RAC values are presented within RAM framework in Figure 2 below.

		Severity			
	Mishap	Catastrophic	Critical	Marginal	Negligible
Probability	Frequent	HIGH 1	HIGH 3	SERIOUS 7	MEDIUM 13
	Probable	HIGH 2	HIGH 5	SERIOUS 9	MEDIUM 16
	Occasional	HIGH 4	SERIOUS 6	MEDIUM 11	LOW 18
	Remote	SERIOUS 8	MEDIUM 10	MEDIUM 14	LOW 19
	Improbable	MEDIUM 12	MEDIUM 15	MEDIUM 17	LOW 20

Figure 2. Risk Assessment Matrix (RAM) used to assess the level of operational risk

RAC values were determined based on the response rate consensus. These classifications are separated by the four RAM levels, as indicated by the color legend of the matrix. Red cells of the matrix are considered High risk. Orange cells are considered to be Serious risk while yellow cells are considered Medium risk. Green cells of the matrix represent Low risk. The resulting RAC classification values for each of the thirty-six tasks are presented in Figure 3.

Task	Probability	%	Severity	%	RAC
Disable an improvised explosive device in a highly populated hostile environment.	FREQUENT	39.2	CATASTROPHIC	58.8	1
Disable an improvised explosive device in a highly populated urban environment.	PROBABLE	49.0	CATASTROPHIC	64.7	2
Disarm an improvised explosive device in a highly populated urban environment.	PROBABLE	43.1	CATASTROPHIC	62.7	2
Disable an improvised explosive device by emplacing 4lbs of counter explosives.	FREQUENT	33.3	CRITICAL	64.7	3
Disarm an improvised explosive device in a dangerous environment.	FREQUENT	47.1	CRITICAL	45.1	3
Search for suspected explosive devices in a mall.	OCCASIONAL	43.1	CATASTROPHIC CRITICAL	35.3	4
Disturb the objects surrounding a potential explosive device.	PROBABLE	45.1	CRITICAL	54.9	5
Disturb the objects surrounding an improvised explosive device.	PROBABLE	39.2	CRITICAL	56.9	5
Identify improvised explosive devices in a difficult field with steep terrain.	PROBABLE	37.3	CRITICAL	56.9	5
Identify improvised explosive devices in a hostile environment.	PROBABLE	41.2	CRITICAL	47.1	5
Quietly search inside of a three-story building for a person being held hostage.	PROBABLE	41.2	CRITICAL	62.7	5
Remove a bomb from a person being held hostage.	PROBABLE	41.2	CRITICAL	47.1	5
Search for suspected explosive devices in a hostile environment.	PROBABLE	43.1	CRITICAL	56.9	5
Search inside a subway tunnel for a bomb.	PROBABLE	35.3	CRITICAL	37.3	5
Disarm an improvised explosive device in a hostile environment.	FREQUENT OCCASIONAL	33.3	CRITICAL	47.1	3/6
Identify improvised explosive devices on the main road of travel.	PROBABLE OCCASIONAL	18.0	CRITICAL	41.2	5/6
Search for a target inside of a vacant three-story building that has no electricity.	OCCASIONAL	35.3	CRITICAL	39.2	6
Quietly search inside of a one-story building for a person being held hostage.	OCCASIONAL	39.2	CRITICAL	54.9	6
Provide visual surveillance outside the door of a suspected terrorist organization for 10 hours.	OCCASIONAL	41.2	CRITICAL	37.3	6
Search underneath a compact vehicle for an explosive devise.	OCCASIONAL	39.2	CRITICAL	47.1	6
Search inside a vacant tunnel for a bomb.	OCCASIONAL	41.2	CRITICAL	41.2	6
Disable an improvised explosive device by emplacing 10lbs of counter explosives.	OCCASIONAL	31.4	CRITICAL	54.9	6
Communicate to a person being held hostage.	OCCASIONAL	43.1	CRITICAL MARGINAL	41.2	6/11
Search for a target inside of a vacant one-story building that has no electricity.	OCCASIONAL	33.3	MARGINAL	45.1	11
Inspect a target of interest inside a cluttered room.	OCCASIONAL	45.1	MARGINAL	51.0	11
Provide audio and visual surveillance outside the door of a suspected terrorist organization.	OCCASIONAL	43.1	MARGINAL	41.2	11
Provide audio and visual surveillance inside the building of a suspected terrorist organization.	OCCASIONAL	35.3	MARGINAL	43.1	11
Remove a 30lbs object off of a person.	OCCASIONAL	41.2	MARGINAL	47.1	11
Remove the restraints from a person being held hostage.	OCCASIONAL	49.0	MARGINAL	31.4	11
Inspect underneath a semi-truck for a bomb.	OCCASIONAL	49.0	MARGINAL	45.1	11
Transport stable explosives from a building.	OCCASIONAL	39.2	MARGINAL	47.1	11
Provide visual surveillance outside the door of a suspected terrorist organization for 2 hours.	REMOTE	39.2	MARGINAL	42.1	14
Monitor a room for human movement.	REMOTE	37.3	NEGLIGIBLE	49.0	19
Monitor a building for human movement.	REMOTE	43.1	NEGLIGIBLE	43.1	19
Remove 30lbs of small rocks off of a person.	REMOTE	31.4	NEGLIGIBLE	33.3	19

Figure 3. Risk assessment results for the thirty-six tasks evaluated during Experiment 1.

In addition to assessing operational risk, each task was examined in terms of robot use. Tasks were identified for each robot based on likelihood of use and selected in terms of the highest and lowest response percentages. Thus, resulting in six capability-based task parings unique for each robot in terms of *High* and *Low* likelihood of use (see Appendix A). In order verify there was a clear capability-based distinction, an independent *t*-test was conducted between use categories for each robot. The results indicate there was a significant difference between the high likelihood of use and low likelihood of use tasks categories for each robot. Results are as followed:

- **Dragon Runner**. Search for a target inside of a vacant one-story building that has no electricity (M = 5.64, SD = 1.48) Disarm an improvised explosive device in a dangerous environment (M = 2.17, SD = 1.96), $t(52) = 7.21$, $p = .000$.
- **510 Packbot**. Disarm an improvised explosive device in a hostile environment (M = 5.15, SD = 1.26) Remove a 30lbs object off of a person (M = 3.58, SD = 2.19), $t(49) = 3.19$, $p = .003$.
- **Armadillo**. Search inside a vacant tunnel for a bomb (M = 5.35, SD = 1.81) Disable an improvised explosive device by emplacing 10lbs of counter explosives (M = 2.25, SD = 2.25), $t(48) = 6.03$, $p = .000$.
- **Firstlook**. Search inside a vacant tunnel for a bomb (M = 5.96, SD = 1.17) Remove the restraints from a person being held hostage (M = 2.14, SD = 1.77), $t(52) = 9.01$, $p = .001$.

- **ReconScout**. Search underneath a compact vehicle for an explosive device (M = 5.96, SD = 1.17) Transport stable explosives from a building (M = 2.14, SD = 1.77), $t(48) = 5.08$, $p = .001$.
- **Talon**. Remove 30lbs of small rocks off of a person (M = 5.44, SD = 1.72) Quietly search inside of a three-story building for a person being held hostage (M = 3.09, SD = 2.25), $t(47) = 4.15$, $p = .001$.

As the first of two experiments, it was also important to discover whether participants found the content in the *Robot Profiles* useful. Multiple regression analysis was conducted to examine the usefulness of the *Robot Profile* contents during task evaluations based on the overall importance ratings. The *Robot Profile* Manufacturer Specifications were shown to be useful during task evaluations producing an $R^2 = .75$, $F(7.49, 0.49) = 15.32$, $p = .001$. The *Robot Profile* Photos were also shown to be useful during task evaluations producing an $R^2 = .79$, $F(6.75, 0.36) = 18.53$, $p = .001$. On average, the *Robot Profile* Manufacturer Specifications (M = 6.00, SD = 1.27) were slightly more important during task evaluations than the *Robot Profile* Photos (M = 5.78, SD = 1.18), $t(97) = 1.98$, $p = .025$, $d = .18$; yet both the *Robot Profile* $t(49) = 34.55$, $p = .001$, and the Manufacturer Specifications $t(50) = 33.88$, $p = .001$, were shown to aid participants.

Discussion

Experiment 1 was designed to empirically refine the experimental methodology for Experiment 2. Considering that the intention was to focus on high-risk applications in which robots are employed to conduct dangerous operations, the risk assessment revealed 39% of the thirty-six tasks generated were considered *High* risk. This finding suggests that participants understood the perceived risks associated with various operational environments, without forced manipulations and independent of robot use.

Tasks were collated for each robot based on likelihood of use in terms of response percentage. Following a subset of six tasks was selected for each robot based on the *high* and *low likelihood of use.* Though more tasks could be selected, if other variables were of interest, six tasks were deemed to be sufficient for the purposes of the intent of research to follow. Despite the small sampling of tasks for each robot, the results indicated a clear differentiation between task-based robot use categories.

Participants also indicated the positive utility of the *Robot Profiles*, and were able to effectively use the information that was provided throughout the robot task evaluations. Thus, both the photo and the manufacturer specifications were deemed helpful decision aids. More interestingly, the results indicated that participants found the Manufacturer Specifications integral during task evaluations.

Experiment 2

Experiment 2 sought to investigate factors affecting robot use; more specifically, the effect of HRI trust and operational risk on the likelihood of robot use. Utilizing a methodology similar to Experiment 1, participants were instructed to assess the likelihood of robot use; however, in this experiment participants were in one of six conditions intended to manipulate HRI trust and operational risk.

The overall design of the study was a 3 x 2 between-subjects design. The independent variables were HRI trust (high, medium, low) and operational risk (high, low). In the experimental trials, participants were instructed to complete task-based evaluations for each robot in likelihood of use. Similar to Experiment 1’s paradigm, the sequence of robots and task presentation order were both randomized, and the experiment concluded after all robots were evaluated.

Method

Participants. 329 participants (Males = 217; Females = 112), between the ages of 18 and 66 (M = 30 years old), were recruited using a crowdsourcing web service, Amazon, Inc. Mechanical Turk (http://www.mturk.com). All participants resided in the United States and had an acceptance rate (i.e., successful completion of previous Human Intelligence Tasks or "HITs") greater than 95%. The average completion time for the study was 35 minutes, and participants were compensated $0.80.

Materials. During the experiment, participants were instructed to use the *Robot Profiles* provided to evaluate each robot; however, the *Robot Profiles* in Experiment 2 incorporated two additional components: (1) robot performance history; and (2) assessed operational risk. In order to assist participants with their evaluations, robot operators rated the overall performance of each robot based on their previous experience, hypothetically speaking. As shown in Figure 4 robot performance histories were generated using yellow stars to indicate favorable robot performance to imply three levels of HRI trust. The second *Robot Profile* addition was replicated results from an operational risk assessment previously conducted, also shown in Figure 4. HRI trust and operational risk remained constant throughout each experimental trial. Other than the two noted *Robot Profile* modifications, all materials used were the same as in Experiment 1.

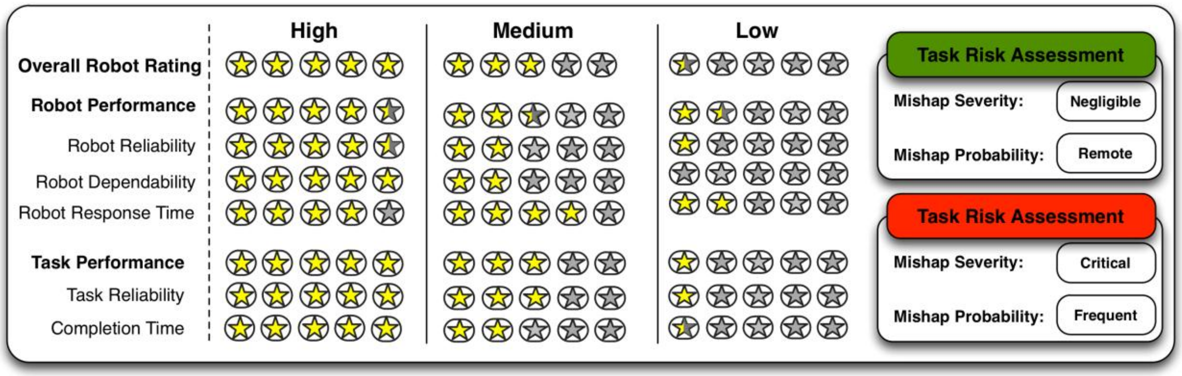

Figure 4. HRI trust (left) and operational risk (right) manipulations integrated into the *Robot Profiles* used during Experiment 2.

Procedure. Prior to starting the experiment, participants were asked to use their knowledge and experience to answer general questions pertaining to robots. Following that introduction, the training session began. The goal of the training session was to familiarize participants with the *Robot Profiles* used in the study. Participants were asked to match the profile content with the following terms: *Robot Capabilities*, *Operator Evaluation*, *Operational Risk*. The training concluded when the participant correctly matched all of the terms to the profile content.

Once the training had been completed, participants were given the experimental instructions. Participants were informed that they would be evaluating the potential use of 6 different robots. Again, instructed to answer the robot use questions referencing the information provided in the *Robot Profiles*, which were unique for each robot.

The six capability-based task parings, as identified in Experiment 1, were utilized to examine the hypothesized effects of HRI trust and operational risk on the likelihood of robot use. For each of the six tasks, participants rated the robot *effectiveness, usefulness,* and *ease of use*; then, similar to Experiment 1, participants were also asked to rate the *likelihood of use* by indicating the extent to which they agree with the following statement: *If I needed to accomplish this task, and the choice was up to me, I would use this robot*. These capability-based items were generated from the psychometric evaluation of various technology acceptance measures conducted by Chin et al. in 2008. Once all robots had been evaluated there was a second administration of the general robot use questions at the conclusion of the experiment.

Results

Robot Configuration. Throughout the experiment, six unique tasks were evaluated for each robot, and of the six tasks, only half of which the robots were properly configured for. More specifically, the configuration of each robot was evaluated in terms of the *effectiveness*, *usefulness*, *ease of use*, and *likelihood of use* for all six tasks. In general, these response items were used to assess the likelihood of robot use relative to the system capabilities required to complete the task.

An exploratory factor analysis with a varimax rotation was conducted to assess the capability-based differences across response items. As shown in *Table 1*, the results indicate a clear separation between the tasks robots were properly configured for (M = 312.90, SD = 55.55) and not properly configured for (M = 239.05, SD = 78.11) accounting for 90% of the variance, ($t(710) = 14.53$, $p = .001$).

Table 1. *Factor Loadings for Exploratory Factor Analysis with Varimax Rotation of Capability-based Robot Evaluation Items*

	Properly Configured	Not Properly Configured		
Response Item	*F*	*F*	*M*	*SD*
Robots that were properly configured to complete the task.				
Effectiveness	**.974**	.094	78.51	14.53
Usefulness	**.962**	.128	80.08	14.81
Ease of Use	**.958**	.107	75.66	15.33
Likelihood of Use	**.955**	.088	60.56	20.30
Robots that were not properly configured to complete the task.				
Effectiveness	.089	**.951**	60.40	19.89
Usefulness	.095	**.944**	61.29	20.27
Ease of Use	.133	**.901**	56.80	20.50
Likelihood of Use	.080	**.928**	78.65	15.07

Furthermore, the capability-based response items within both robot configuration groups identified were all positively correlated, with *r*-values ranging from .71 to .92 and $p = .001$. Based on these results, the highly correlated capability-based response items were collapsed then separated into two robot configuration categories. A within-subjects analysis of variance (ANOVA) was conducted to assess the actual degree of difference between the two configuration categories that were established. The results confirmed there was significant difference between the two consolidated groups of capability-based response items, $F(1, 355) = 263.72$, $p = .001$, $\eta^2 = .43$.

To permit a more streamlined presentation, the description of the likelihood of robot use results herein focuses more, but not exclusively, on the robot configuration composite scores (e.g., *effectiveness*, *usefulness*, *ease of use*, and *likelihood of use* were combined based on task ability, respectively) identified. Therefore, the effects of HRI trust and operational risk, on the likelihood of robot use, will be analyzed separately for robots properly configured and not properly configured to complete the task.

HRI Trust. As stated in Hypothesis 1, HRI trust was expected to have a positive main effect on the likelihood of robot use. To assess the extent to which HRI trust affected robot use, the results were analyzed between robot configuration categories using the composite ratings previously identified. The results identified significant variations in the likelihood of robot use associated with HRI trust when the robot was properly configured ($F(2, 350) = 28.931$, $p = .001$, $\eta^2 = .14$), and when the robot was not properly configured ($F(2, 350) = 29.55$, $p = .001$, $\eta^2 = .14$) to complete the task. Consonant with this finding, as was predicted in Hypothesis 1, there was a positive relationship between robot use and HRI trust. As shown in Figure 5, this relationship held true for both robots properly configured ($r = .340$, $p = .001$) and not properly configured ($r = .302$, $p = .001$) for the task.

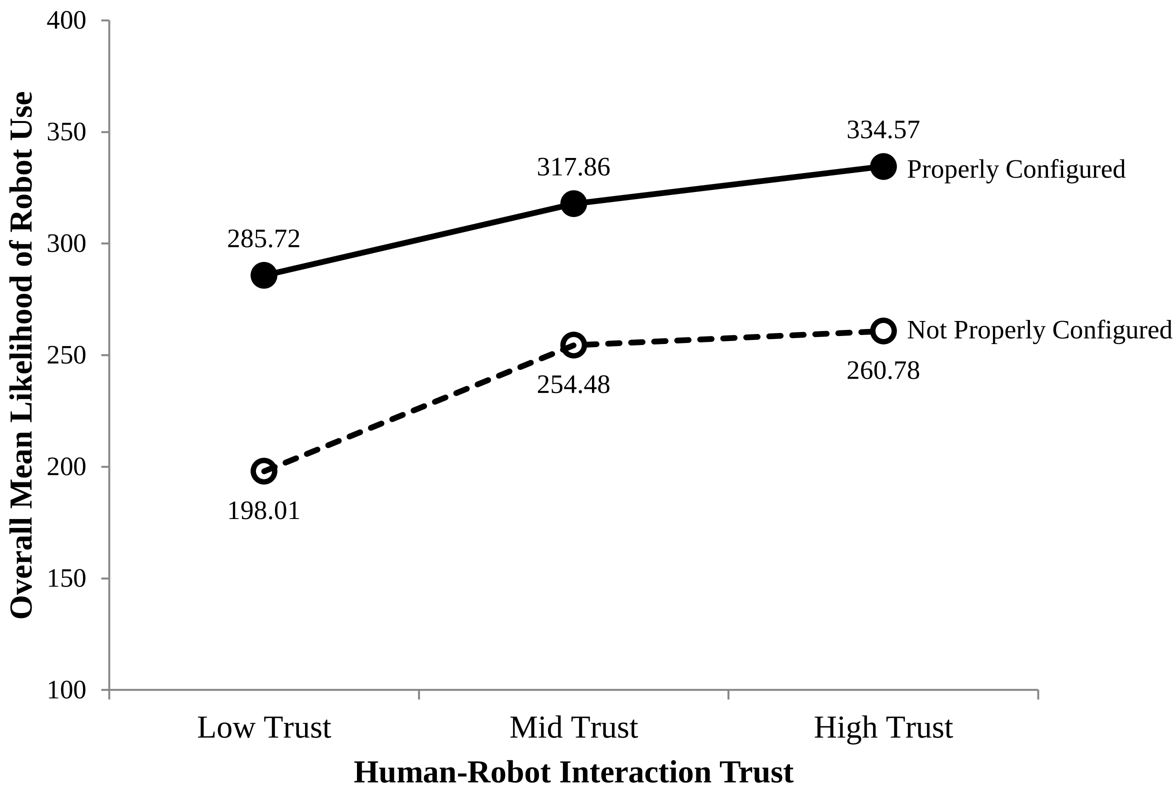

Figure 5. The impact of HRI trust on the likelihood of robot use. The results presented have been separated between robots properly configured and not properly configured.

In order to further investigate Hypothesis 1, additional post-hoc analyses were conducted to decompose the main effect of HRI trust on robot use. LSD comparisons identified a significant difference between all levels (High, Medium, Low) of HRI trust for robots properly configured, ranging from p = .001 to .023. Revealing a higher likelihood of robot use as HRI trust increases. When robots were not properly configured, similar likelihood of use differences were found between *High* and *Low* HRI trust (p = .001); however, no significant difference between *High* and *Medium* HRI trust (p = .473) was found. Interestingly, there seems to a ceiling effect, at higher levels of HRI trust, when a robot is not properly configured.

Operational Risk. Hypothesis 2 claimed that operational risk would have a negative impact on the likelihood of robot use. As shown in Figure 6, there was a significant main effect of operational risk on robot use when properly configured, $F(1, 350) = 5.21$, $p = .023$, $\eta^2 = .02$, and when not properly configured, $F(1, 350) = 12.38$, $p = .001$, $\eta^2 = .03$, to complete the task. Interestingly enough, when the results were analyzed between operational risk levels for each robot configuration category, this main effect was only partially supported. When a robot was not properly configured, operational risk had a significant impact on the likelihood of robot use, $F(1, 355) = 6.13$, $p = .014$. Consistent with Hypothesis 2, the findings indicated that higher operational risk resulted in a lower likelihood of robot use ($r = -.131$, $p = .014$) when a robot was not properly configured to complete the task. However, operational risk did not have an effect on robot use if properly configured, $F(1, 355) = 1.555$, $p = .213$. This lack of variation in use suggests that if a robot is properly configured for the task operational risk alone will not have an effect, $r = -.066$, $p = .213$.

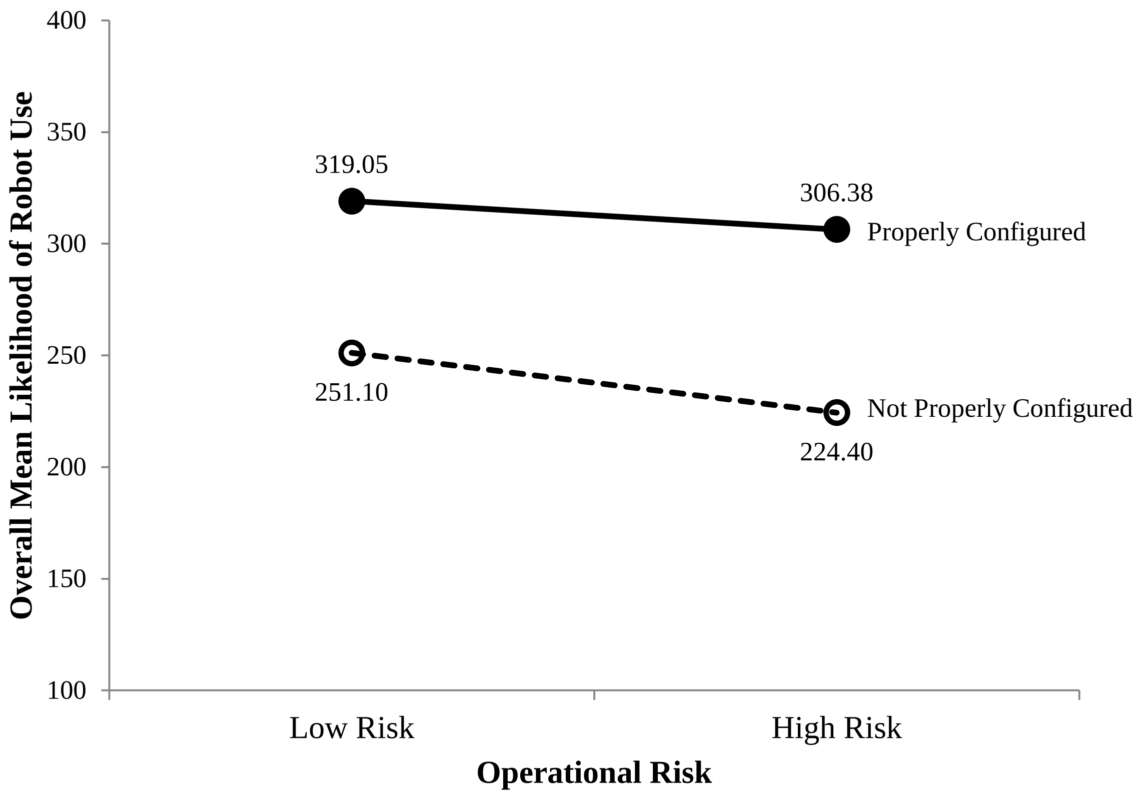

Figure 6. The impact of operational risk on the likelihood of robot use. The results presented have been separated between robots properly configured and not properly configured.

HRI Trust and Operational Risk. Hypothesis 3 stated that operational risk was expected to moderate the effect of HRI trust had on the probability of robot use. In order to assess this hypothesize effect a multiple regression was conducted, and the results were again analyzed between robot configuration categories. The findings are presented in *Table 2* between robot configuration categories.

Table 2. *Multiple Regression Analysis Predicting Robot Use from HRI Trust and Operational Risk with Robots Properly Configured and Not Properly Configured*

	Properly Configured			Not Properly Configured		
Predictor	*B*	*SE*	*β*	*B*	*SE*	*β*
HRI Trust	23.591	3.269	.362**	30.501	4.508	.103**
Operational Risk	-14.474	5.569	-.130**	-29.548	7.674	-.059**
Trust x Risk	13.305	6.539	.100*	41.181	9.017	.070**
R^2		0.15			0.20	

Overall, when properly configured there was a significant interaction between HRI trust and operational risk, $F(2, 350) = 5.57$, $p = .004$, $\eta^2 = .03$. Furthermore, there was also a significant interaction found when the robot was not configured properly for the task, $F(2, 350) = 15.06$, $p = .001$, $\eta^2 = .08$. As shown in Figure 8, robot use increased with HRI trust and decreased when operational risk increased. Similarly, these results held when robots were properly configured and not properly configure to complete the task. In order to further investigate the interaction between HRI trust and operational risk on robot use additional post hoc analyses were conducted on findings of particular interest to Hypothesis 3.

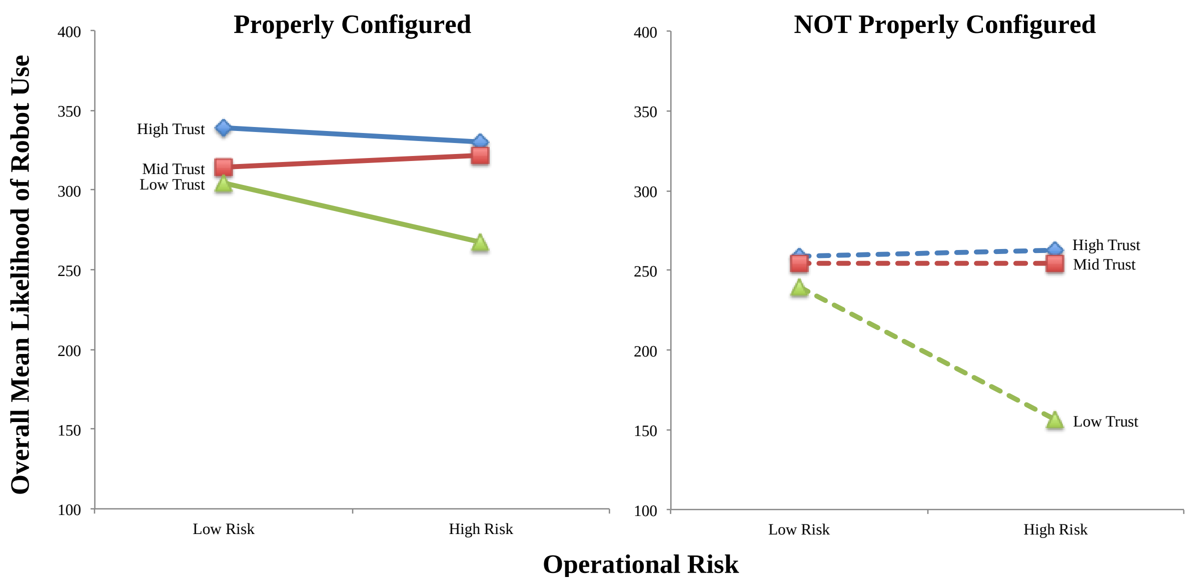

Figure 7. The overall interaction between HRI trust and operational risk on the likelihood of robot use. The results presented have been separated between robots properly configured and not properly configured.

In order to further investigate Hypothesis 3, a closer look was taken at the interaction between HRI trust and operational risk. Considering there was an instance when no difference was found between *High* and *Medium* HRI trust, the results herein are expressed only in terms of *High* and *Low* HRI trust. As shown in Figure 9, variations in operational risk did not seem to cause a significant change in robot use when HRI trust was *High*. In fact, this finding held for robots both properly configured ($t(125) = 1.13$, $p = .261$) and not properly configured ($t(125) = 0.28$, $p = .778$) suggesting that operational risk does cause variations in robot use when HRI trust is *High*. Yet, there was a significant change in likelihood of robot use between the robot configuration categories in low operational risk ($t(96) = 6.29$, $p = .001$) and high operational risk ($t(154) = 6.69$, $p = .001$) conditions (see Figure 9).

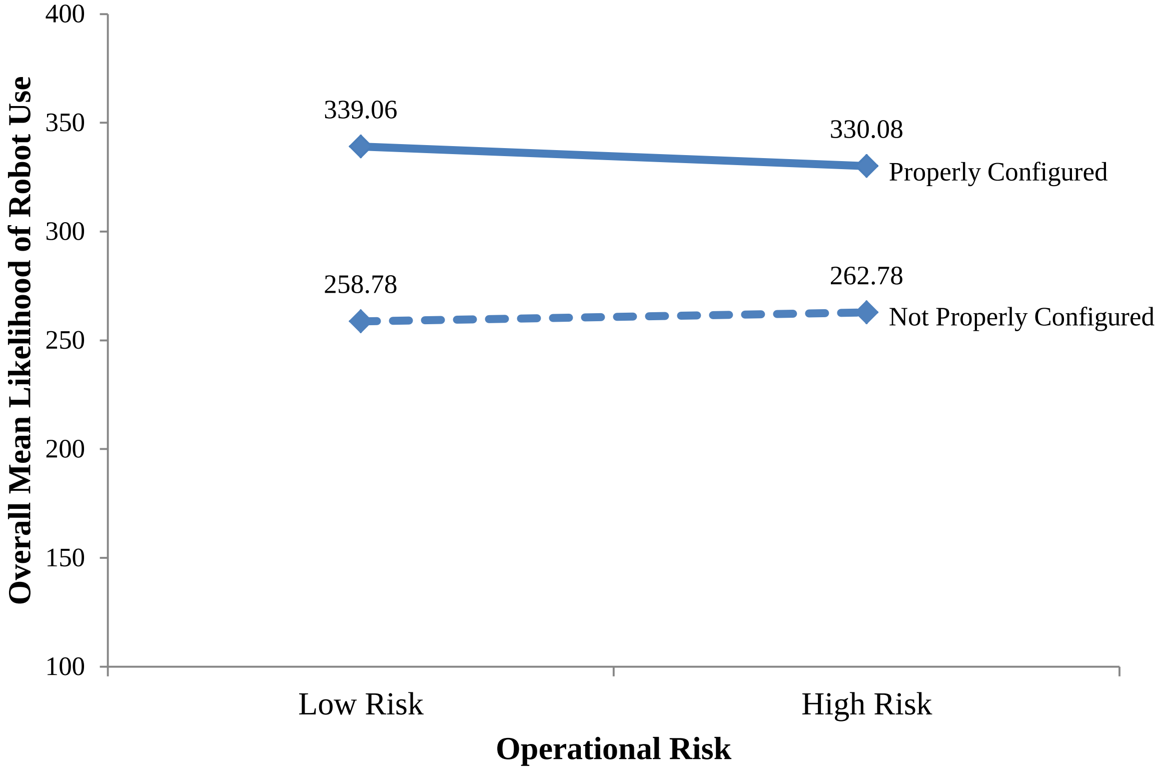

Figure 9. The likelihood of robot use across operational risk conditions when HRI trust is *High.* The results presented have been separated between robots properly configured and not properly configured.

Although, operational risk did cause a significant change in robot use when HRI trust was *Low* when robots were properly configured ($t(129) = 3.42$, $p = .001$) and not properly configured ($t(129) = 7.57$, $p = .001$). In addition, there was a significant difference between robot configuration categories in *Low* operational risk ($t(154) = 7.34$, $p = .001$) and *High* operational risk ($t(104) = 8.48$, $p = .001$) pertaining to robot use (see Figure 10). As expected, *Low* HRI trust resulted in a lower likelihood of robot use. Furthermore, this effect was even more pronounced in *High* operational risk situations.

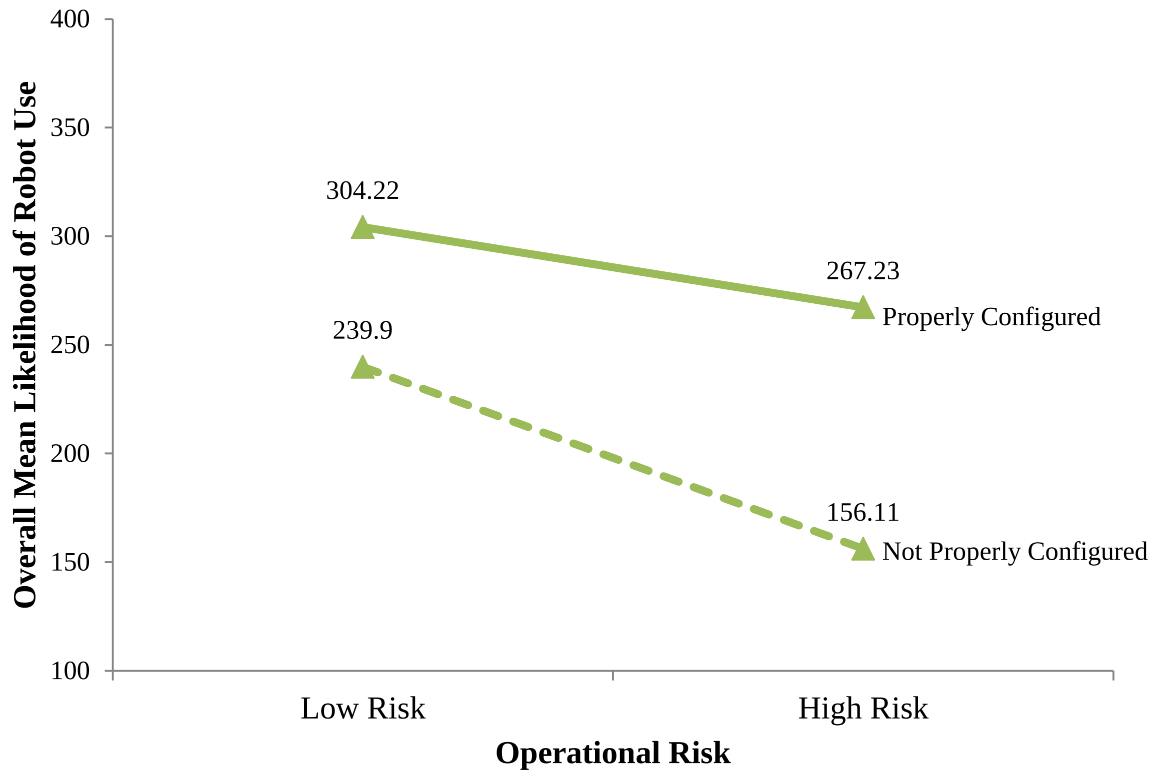

Figure 10. The likelihood of robot use across operational risk conditions when HRI trust is *Low*. The results presented have been separated between robots properly configured and not properly configured.

There was a very interesting interaction found when combining a subset of the results shown in Figure 9 and Figure 10. More specifically, comparing a robot properly configured with *Low* HRI trust to a robot not properly configured with *High* HRI trust (see Figure 11). In a *Low* operational risk situation, there was a higher likelihood of using the robot properly configured (M = 304.22, SD = 47.81) as opposed using to the robot not properly configured (M = 258.78, SD = 76.50) to compete the task, $t(125) = 4.12$, $p = .001$. Ideally, this is what should be expected. However, it is quite concerning that this is not the case in *High* operational risk situations. Actually, no difference was found between using a robot properly configured (M = 267.23, SD = 76.15) and using a robot not properly configured with *High* HRI trust (M = 262.78, SD = 78.27) in a *High* operational risk situation, $t(129) = .323$, $p = .747$ (see Figure 11). Interestingly, it seems these results have concluded the opposite of Hypothesis 3 to be true; where, HRI trust actually moderates the effect of operational risk has on robot use.

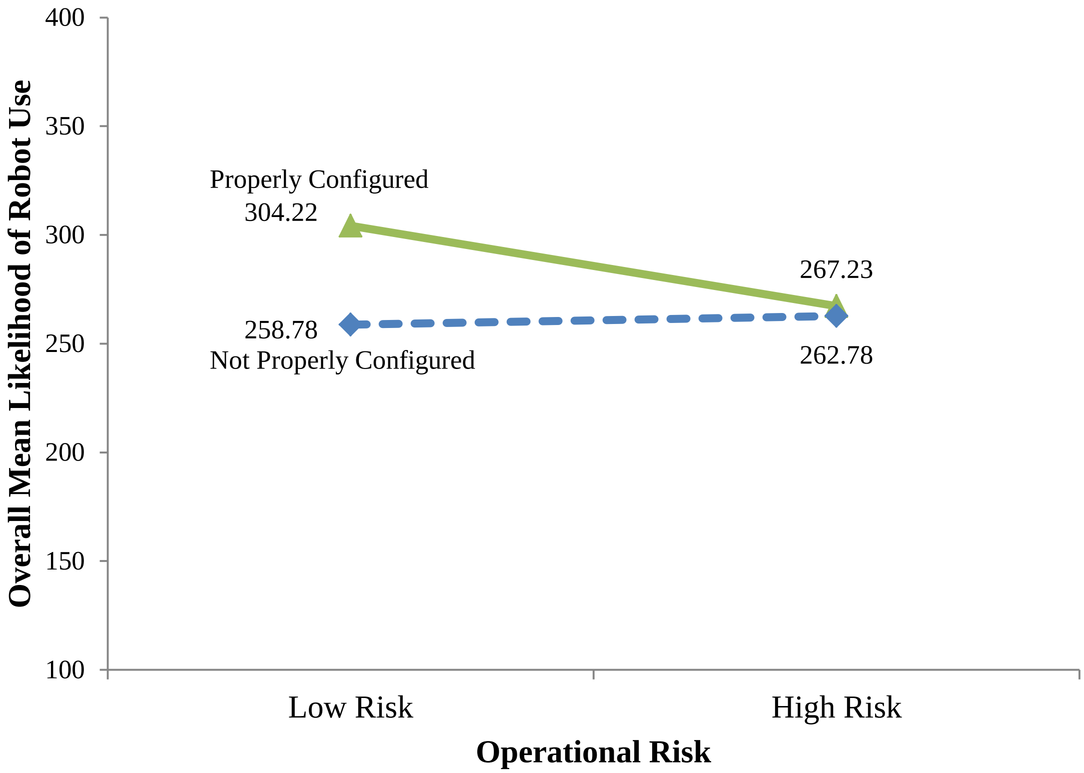

Figure 11. The likelihood of using a robot properly configured with Low HRI trust compared to using a robot not properly configured with High HRI trust across operational risk conditions.

Discussion

The results from the second experiment highlighted the influence of HRI trust and operational risk on the likelihood of robot use; in addition, they shed light on the importance of the configuration of the robot capabilities needed for task completion. Hypothesis 1 attributed a positive relationship between HRI trust and robot use and was confirmed. Overall, there was a higher likelihood of robot use with increasing HRI trust. Furthermore, when there were high levels of HRI trust, changes in operational risk did not affect likelihood of robot use. Considering the positive interaction was maintained, this bolsters the evidence in support of Hypothesis 1 when a robot is properly configured for the task.

Hypothesis 2 examined the relationship between operational risk and likelihood of robot use. The experimental results only partially confirmed the negative relationship initially proposed. There was no isolated significant difference found for operational risk when robots were configured properly there was, however, for when they were not configured properly. Yet, taking into account the entire operational picture there was a significant main effect of operation risk for both task-based robot configuration categories. Thus, full operational impact of risk warrants further articulation and testing in the future. For the purposes of this research, operational risk findings seem to become more meaningful within the context of HRI trust within Hypothesis 3.

In Hypothesis 3 operational risk was expected to moderate the effect HRI trust has on the likelihood of robot use. The examination of operational risk moderating the effects HRI trust yielded some surprising results. At high HRI trust levels there was no change in likelihood of robot use even if the robot was not properly configured, comparatively speaking. A negative, significant interaction was found with low levels of HRI trust displaying a much stronger positive association between HRI trust and robot use with high levels of operational risk; which, was heightened when the robot was not properly configured. One could infer there is a high probability of failure associated with using a robot not properly configured; which, would then ultimately lead to serious operational consequences during dangerous operations. Thus, HRI trust can have both a positive and negative influence in terms of the operational risks associated with on robot use.

General Discussion

This study examined underlying factors affecting the likelihood of robot use. The overall intent of Experiment 1 was to identify high-risk tasks, in which each of the six robots would or would not be used for. In doing so, empirically refine the experimental methodology that was used in Experiment 2. Experiment 2 sought to investigate three hypothesized effects of HRI trust and operational risk on the likelihood of robot use. Hypothesis 1 examined the effect of HRI trust on robot use, attributing a positive relationship between the two progressive variables. When a robot was properly configured for the task, the data was strongly consistent with Hypothesis 1. However, when not properly configured, the likelihood of robot use seemed to plateau instead of progressively increasing with HRI trust. Concluding that HRI trust increases the likelihood of robot use with the proposition that this relationship is moderated by the capabilities of the robot configuration.

The data was only marginally consistent with Hypothesis 2, which examined the notion that an increase in operational risk leads to a lower likelihood of robot use. There was a significant negative interaction between robot use and operational risk, which is consistent with Hypothesis 2; however, this relationship only held when a robot was not properly configured for the task. When a robot was properly configured, an increase in operational risk did not yield a significant change in robot use. Thus, variations in robot use were shown to be mainly associated with the capabilities of the robot as opposed to the sequestered operational risk context.

Examining the interaction between HRI trust and operational risk, as noted in Hypothesis 3, yielded some surprising results pertaining to tendencies in robot use. The data revealed that in a high operational risk situation, HRI trust becomes a significant factor in determining which robot (i.e., properly configured or not properly configured) to use. In fact, instances when HRI trust is high may lead to using a robot that is not even properly configured for the task. In addition, there was no significant difference between that and using a robot properly configured when HRI trust was low. Thus, a person is just as likely to use ‘an old reliable’ robot that does not have the capabilities needed to complete the task, just because it is a trusted system. As always, the results of one study should be interpreted with some reservation, but there could be serious consequences if this tendency or unwillingness to accept new unmanned systems were to hold during an actual high-risk operation. The underlying mechanisms associated with the process in which this propensity develops warrant further articulation and testing in future research.

In order to enhance the utility and acceptance of unmanned systems, better HRI is needed. It is beneficial to understand the underlying mechanisms that influence the perception (right or wrong) surrounding a new or existing unmanned system in an operational environment. Considering the laboratory nature of this research, the generalizability is limited. Although, the results from this research do provide an adequate foundation for investigating operational factors highly associated with the acceptance and use of new unmanned systems.

The results from this research allude to some of the operational challenges faced when employing new and unproven robots. First, the unmanned system capabilities need to match the demands of the mission and complement operator performance. In order to start building operational trust, the robot must first be properly configured to execute the mission. Based on the findings of this research, there is a higher likelihood of robot use when the functional capabilities align with the demands of the task; however, this is not always the case. Evidence has suggested that HRI trust is needed to maintain the human-robot collaboration needed to effectively complete the mission. Thus, a lack of HRI trust may lead to unintended consequences analogous with inappropriate robot use decisions.

Building and maintaining HRI trust within an operational environment is a relatively new concept, and quickly emerging. “Developing operational trust between the users and the autonomous systems will require education and comprehensive training of the human-autonomy teams,” (pg. 64; Defense Science Board, 2012). Additional research is needed to investigate how HRI trust can be evaluated and monitored during human-robot collaborations. A few future research questions to ponder:

- Are operators taking on more risk to themselves in order to use their favorite ‘old reliable’ robot?
- How have previous interactions influenced the preconceived notions towards a new system or using new autonomous capability intended to enhance the functionality of a system?

- At what point does an operator no longer trust a robot, disregard the system, and complete the task themselves?
- What is the short term and long term impact of a system behaving unexpectedly or failing suddenly during a critical phase of a mission?

At many levels there have been obstacles towards gaining general acceptance of unmanned systems. For instance, there has been a prevalent misperception, throughout the general population, that robots are running around making independent decisions, taking uncontrolled actions with no human(s) in-the-loop (i.e., skynet). Collectively, a lack of trust has developed making it difficult to obtain approvals for proper test and evaluation of new systems or in some cases support for resourcing the acquisition of a new system. As a result, this has limited the potential adoption by creating a natural fear of a new and unproven autonomous technology with concerns about safety (DSB Autonomy Report, 2012).

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APPENDICES

Appendix A

Robot Task Parings Identified in Experiment 1

A.1 Dragon Runner

Manufacturer Specs

Size	**Weight:** 11 lbs **Height:** 15 cm **Length**: 15.5" **Width:**13.8"x6"
Control	Compatible with all existing QinetiQ controllers
Sensors	Cameras (Front & Rear): Day and Night capable
Payload	N/A
Manipulator	N/A
Power Source	On board battery
Endurance	2-3 Hrs, mission dependent

High Likelihood of Use

Search for a target inside of a vacant one-story building that has no electricity.	*Strongly Agree*	36.0%	
Search inside a subway tunnel for a bomb.	*Strongly Agree*	28.0%	
Search for suspected explosive devices in a hostile environment.	*Agree*	37.0%	

Low Likelihood of Use

Disarm an improvised explosive device in a dangerous environment.	*Strongly Disagree*	65.5%	
Remove 30lbs of small rocks off of a person.	*Strongly Disagree*	65.2%	
Remove a 30lbs object off of a person.	*Strongly Disagree*	63.0%	

A.2 510 Packbot

Manufacturer Specs

Size	**Width:** 20.5 in **Length**: 27 in **Height**: 12.0 in **Weight**: 58.8 lbs
Control	Eyes-on, remote teleop, preset poses
Sensors	LWIR Thermal Camera, Camera Arm "CAM": 5.8 lbs (2.6 kg)
Payload	Enhanced Aware Payload "EAP": 2.5 lbs (1.1 kg
Manipulator	4 DOF, Small Arm Manipulator "SAM": 8.2 lbs
Power Source	Battery: Batteries (2 BB-2590s): 6.3 lbs (2.9 kg)
Endurance	Approximately 4 hours

High Likelihood of Use

Search inside a vacant tunnel for a bomb.	*Strongly Agree*	38.5%	
Inspect underneath a semi-truck for a bomb.	*Strongly Agree*	29.6%	
Monitor a building for human movement.	*Agree*	50.0%	

Low Likelihood of Use

Disable an improvised explosive device by emplacing 10lbs of counter explosives.	*Strongly Disagree*	62.5%	
Disable an improvised explosive device in a highly populated urban environment.	*Strongly Disagree*	61.5%	
Remove 30lbs of small rocks off of a person.	*Strongly Disagree*	60.0%	

A.3 Armadillo

Manufacturer Specs

Size	**Height:** 7.95 in **Width**:10.43in **Length:** 1.00 in **Weight:** 5.50 lb
Control	Remote tele-op, mobile, electro optic
Sensors	5 day/night cameras with 4x zoom, delivering a 360° FOV
Payload	N/A
Manipulator	N/A
Power Source	External 12v power and data connector, Li-Ion batteries
Endurance	1.5 hours full operating condition and 12 hours standby mode

High Likelihood of Use

Search inside a vacant tunnel for a bomb.	*Strongly Agree*	38.5%	
Inspect underneath a semi-truck for a bomb.	*Strongly Agree*	29.6%	
Monitor a building for human movement.	*Agree*	50.0%	

Low Likelihood of Use

Disable an improvised explosive device by emplacing 10lbs of counter explosives.	*Strongly Disagree*	62.5%	
Disable an improvised explosive device in a highly populated urban environment.	*Strongly Disagree*	61.5%	
Remove 30lbs of small rocks off of a person.	*Strongly Disagree*	60.0%	

A.4 FirstLook

Manufacturer Specs

Size	**Weight:** Less than 5 lbs **Height:** 4 in **Length**: 10 in **Width**: 9 in
Control	Game style Control with radio & collapsible antenna
Sensors	4 built-in cameras: front, rear and side-facing, 8X digital zoom
Payload	N/A
Manipulator	N/A
Power Source	Lithium Ion battery
Endurance	More than 6 hours on average

High Likelihood of Use

Search inside a vacant tunnel for a bomb.	*Strongly Agree*	44.0%	
Search underneath a compact vehicle for an explosive devise.	*Strongly Agree*	37.5%	
Provide visual surveillance outside the door of a suspected terrorist organization for 2 hours.	*Strongly Agree*	36.4%	

Low Likelihood of Use

Remove the restraints from a person being held hostage.	*Strongly Disagree*	58.6%	
Disable an improvised explosive device in a highly populated urban environment.	*Strongly Disagree*	52.0%	
Transport unstable explosive material from a building.	*Strongly Disagree*	48.0%	

A.5 ReconScout

Manufacturer Specs

Size	**Width:** 3 in **Length**: 7.36 in **Height:** 3 in **Weight:** 1.2 lbs
Control	Remote teleop
Sensors	Infrared, camera
Payload	N/A
Manipulator	N/A
Power Source	11.4 V DC Lithium Polymer
Endurance	60 minutes

High Likelihood of Use

Search underneath a compact vehicle for an explosive devise.	*Strongly Agree*	32.0%	
Search for a target inside of a vacant one-story building that has no electricity.	*Strongly Agree*	24.0%	
Search for suspected explosive devices in a hostile environment.	*Somewhat Agree*	38.5%	

Low Likelihood of Use

Transport stable explosives from a building.	*Strongly Disagree*	56.0%	
Communicate to a person being held hostage.	*Strongly Disagree*	44.4%	
Disturb the objects surrounding a potential explosive device.	*Strongly Disagree*	42.9%	

A.6 Talon

Manufacturer Specs

Size	**Width**: 22 in **Length:** 34 in **Height:** 11-52 in **Weight:** 115 to 140 lb
Control	digital/analog, 500-800 m LOS High Gain antenna range to 1200m LOS
Sensors	Chemsentry , RAE System MultiRAE, Canberra AN- UDR-14, RayTek temp. probe, targeting laser
Payload	100 lb (45 kg)
Manipulator	30 in-lb of gripping strength, 6 in wide opening, manual 340 degree wrist
Power Source	Single Lithium-ion Battery or Dual Lead-Acid Battery Pack
Endurance	4.5 hr (7.2 km/hr)

High Likelihood of Use

Remove 30lbs of small rocks off of a person.	*Strongly Agree*	37.0%	
Disable an improvised explosive device by emplacing 4lbs of counter explosives.	*Strongly Agree*	33.3%	
Disturb the objects surrounding an improvised explosive device.	*Strongly Agree*	30.8%	

Low Likelihood of Use

Quietly search inside of a three-story building for a person being held hostage.	*Strongly Disagree*	45.5%	
Provide visual surveillance outside the door of a suspected terrorist organization for 10 hours.	*Strongly Disagree*	24.0%	
Communicate to a person being held hostage.	*Strongly Disagree*	20.0%	