Trusted Artificial Intelligence for Armaments in Uncertain Environments

Justin Abel[1], Stephen Durham[1], Andrew Evans[1], Hannah Palmer[1], Sami Saliba[1]
Mentored by Hunter Moore[1] and William Scherer[1]

***Abstract*— Navigating minefields presents a critical challenge for ensuring the safety of warfighters, particularly when relying on AI-enabled autonomous systems with inherent uncertainties. Trust in these systems is essential for mission success, as mistakes can have life-or-death consequences. Here we propose a framework for building trust in autonomous minefield traversal systems by integrating explainable statistical models and reinforcement learning into a modular simulation environment. Our approach leverages an agent-based simulation and machine learning to address the dual objectives of accurate mine detection and efficient traversal. We show how statistical methods can quantify the reliability of AI and human predictions under varying environmental conditions and how reinforcement learning can optimize routing decisions in uncertain scenarios. This system provides interpretable outputs, robust risk-based monitoring, and adaptability to changing parameters, demonstrating a feasible pathway toward trustworthy and efficient autonomous minefield navigation.**

I. Introduction

Our goal is to improve trust in Artificial Intelligence (AI) enabled systems through the integration of explainable statistical models into black box AI. Our approach is contextualized through a life critical control problem in the form of minefield traversal.

The challenge involves navigating Unmanned Ground Vehicles (UGVs), Unmanned Aerial Vehicles (UAVs), and warfighters through uncertain terrain and environmental conditions. Mine detection is carried out by the UAV through scans performed by two subsystems: a human subject matter expert (human) and an AI. Both subsystems operate with unknown levels of uncertainty and reliability. While these predictors differ in methodology, they can be treated as environmental factors, providing estimates based on a fixed policy. Trust in this context is defined by the ability to rely on these semi-unreliable subsystems, which represent the non-transparent or "black box" nature of AI systems [1]. The high complexity that gives AI an edge over traditional control and prediction methods comes at the cost of human interpretability, particularly in modeling high-dimensional interactions [2]. In critical scenarios where mistakes can have life-or-death consequences, this lack of transparency is unacceptable.

In this study, we introduce trust into high-complexity AI systems by simplifying data inputs and providing a structured behavioral framework, similar to human decision-making, in the form of a reward function. Informally, the problem is to minimize mine encounters and traversal time in a minefield of N nodes by intelligently routing the UGV and UAV in each scenario. Our approach uses a detailed minefield simulation to train explainable statistical models and a reinforcement learning (RL) algorithm that guides the UAV in selecting scan locations and methods. UGV control relies on a fixed policy routing method informed by mine likelihood and path uncertainty. Traditionally, minefield navigation has relied entirely on human control, which incurs significant costs, operational variability, and substantial time requirements, potentially undermining tactical advantages.

In contrast, our approach adapts quickly to new scenarios, provides explainable statistical outputs and behavior, and effectively manages the variable accuracy of the two prediction subsystems. The primary contribution of this work is the development of a novel mission simulation environment to train an intelligent RL agent using statistical models that estimate the accuracy of mine detection methods. Through this study, we demonstrate methods for integrating trust into AI architectures, enhancing transparency, verifiability, and human understanding of complex control systems.

The rest of this paper is organized as follows. In Section II, we provide a precise problem formulation. Section III presents the relevant background on trust, explainable statistics, and reinforcement learning. In Section IV, we describe our methods, which include a map generation design, accuracy methodologies, prediction estimations, simulation design, and a simulation setup with base parameters. Section V focuses on the development of the intelligent agent, discussing UGV routing, UAV design, a deeper exploration of explainable statistics, and risk-based monitoring. In Section VI, we discuss the experimental design and results, followed by a final section that covers the relevance of this work, future directions, key workforce skills and abilities, and work adoption.

II. Problem Formulation

The overarching goal of this mission context is to establish trust by enabling a system to safely and efficiently clear minefields while minimizing risks and traversal time. This problem is particularly challenging due to the unreliability of the system's subsystems—human and AI detection methods that are not fully accurate. To address this, we decompose the problem into two primary components: establishing a robust mine detection system and minimizing traversal time. Each component is further divided into measurable sub objectives that collectively ensure mission success.

[1] University of Virginia School of Engineering, Department of Systems and Information Engineering

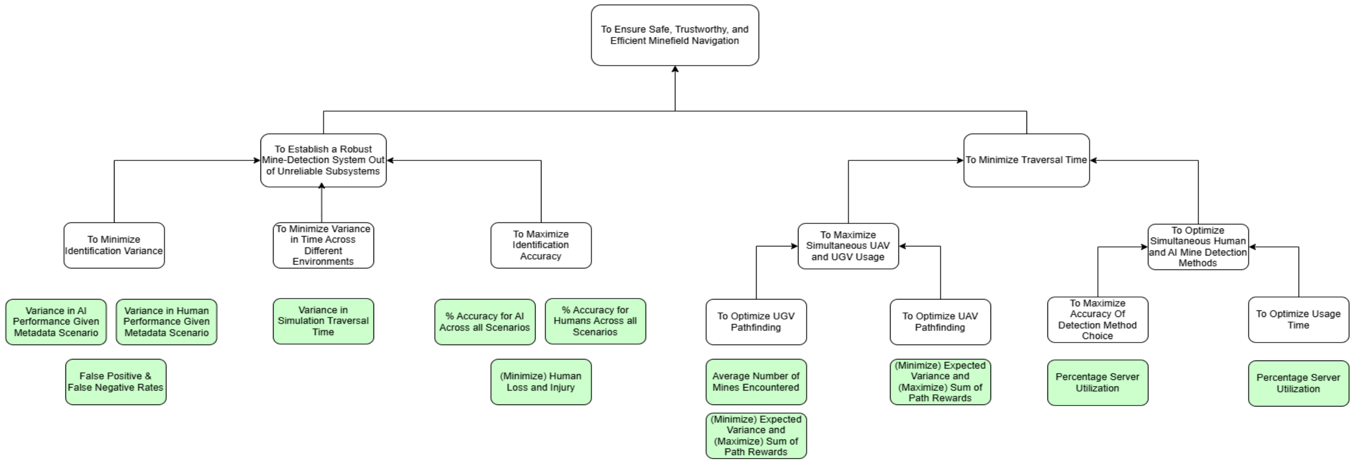

Fig. 1. Objectives Tree for Mission Context

A robust mine detection system is fundamental to mission success and trust building, as it directly addresses the life-threatening risks associated with inaccuracies in mine detection. To enhance the reliability of the detection system, we prioritize the following sub-objectives: minimizing identification variance, maximizing identification accuracy, and minimizing time variance across different environments. These objectives are measured using metrics such as variance levels, percent accuracy, and human injury. Precision and accuracy are critical for ensuring system reliability. Minimizing various measures of variance ensures precision, while high percent accuracy ensures detection reliability. A system that consistently delivers precise and accurate results while minimizing human loss builds confidence in its ability to operate safely and effectively, even in high-stakes scenarios. The second component focuses on optimizing the efficiency of minefield traversal to meet mission objectives within operational constraints. Traversal time is critical to mission success, as delays can compromise safety and operational effectiveness. This objective is divided into two key objectives: maximizing simultaneous use of the UAV and UGV and optimizing human and AI mine detection efforts. Simultaneous usage ensures that resources are optimally utilized, with the UAV imaging new terrain and the UGV continuously moving or disabling any mines encountered, decision makers receive maximal new information while moving towards the mission goal as efficiently as possible. Additionally, human and AI evaluators should continuously analyze images to minimize downtime and maximize efficiency. This ensures a steady flow of data processing and reduces delays in minefield traversal. Maximizing simultaneous UAV and UGV usage requires optimizing their respective pathfinding strategies. Similarly, optimizing human and AI detection methods involves maximizing the accuracy of detection and ensuring their time is used efficiently. These objectives are measured using metrics such as the average number of mines encountered, expected variance and sum of path rewards, and percentage server utilization. These metrics are calculated using reinforcement learning techniques, which ensure optimal system performance. By tying each sub objective to quantifiable metrics, the system will improve its reliability, minimize risks, and strengthen trust at all levels of operation.

A. System Architecture

In developing a system built around trust and user confidence, it is necessary to consider mission contexts and understand how the system operates. Based on the strategies developed to ensure trust and build a reliable system, once the mission begins, troops proceed as outlined in Figure 2. Start and end points are identified and the UAV is used to survey surrounding cells and potential troop movements. The UAV sends images back to the AI and human to determine the optimal routing path, and this message is passed on to the UGV and troops who are sent down the path. From the new location, the UAV performs the same operation, analyzing new paths in the immediate area of the current node and sending information back to the command center. The risk management system determines the optimal path, and the UGV and troops are told to advance to the next optimal cell. This process continues until the endpoint cell is reached. At a more granular level, we also consider the

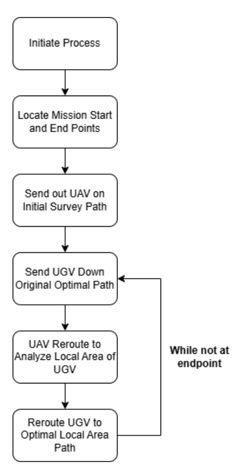

Fig. 2. Mission Context Process for Simulation Modeling

process of traversing between cells in the minefield network. There is some probability that troops and the UGV will encounter a mine on the ground, and understanding the method for either rerouting to a safer path or defusing the mine along a dangerous path is outlined in Figure 3. The UAV sends images to the human and AI systems to determine the probability of a mine being present along a traversal edge. If a mine is predicted to be present, the UAV may continue scanning for a more safe path. At the command center, a decision is made regarding which available edge to traverse. The optimal traversal strategy could include a mix of rerouting away from probabilistically dangerous paths or following down them if costs incurred from rerouting are high. A decision to route the UGV down a path even if the probability of mine presence is high is a possibility, and it will be considered more rigorously in future studies. Regardless, a command is sent for the UGV to be routed and the troops to follow. While traversing the selected edge, the UGV will survey for mines. Unless a mine is identified, troops and the UGV continue on to the next node. If a mine is present, the UGV defuses it with 100% effectiveness and troops continue forwards. In the final stage of the project, the UGV will likely not operate 100% effectively, introducing additional randomness and complications that must be considered in new models and systems.

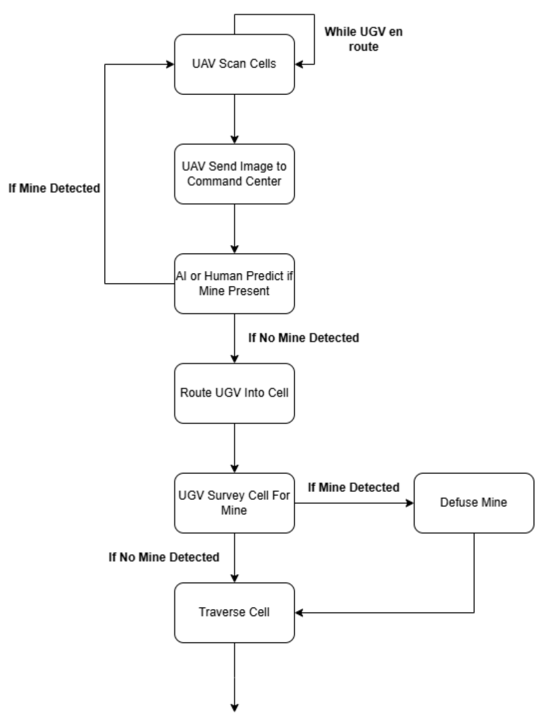

Fig. 3. Network Traversal and Mine Removal Process

III. Background

A. Trust

As adopted from the United States Department of the Army, we define trust as “reliance upon others, confidence in their abilities, and consistency in behavior” [3]. This framework, although originally contextualized for human trust, is extensible to AI control. In the context of an AI-enabled system, trust involves human dependence on the system’s functionality, confidence in its capabilities, and an expectation of consistent and reliable performance. Therefore, trust in such systems is established through its ability to deliver accurate, effective, and consistent outcomes that align with the system’s goals.

In our development of this system, we assume that AI functions as part of a larger, human-involved system. By maintaining human oversight, human control is retained and the AI is prevented from overriding human decisions. The AI acts as a team member—one that is as ethical and trustworthy as the humans responsible for its design and operation. Functionality is predictable, governed by its training and commands; ensuring trust to be established as long as its behavior remains consistent within its design. To build confidence in the system, transparent and auditable statistical models are integrated into its overall design. These models provide a foundation for consistency and predictability. These methods enable operators to monitor performance, identify errors, and reduce the likelihood of error recurrence. The system is able to refine its decision-making processes over time, improving accuracy and reliability. Evidence-based decisions, informed by past performance, help identify and mitigate risks, enabling the system to anticipate challenges and avoid repeating mistakes.

To achieve consistency in the system’s behavior, metrics are being monitored over time to ensure stable performance in a variety of aspects. This allows for early detection of deviations and ensures that the system meets its goals. Monitoring these metrics provides a quantification of trust. Our approach prioritizes robustness and reliability, which are critical in high-risk tasks like minefield traversal, where minimizing risk saves lives. We also focus on transparency and explainability by providing clear reporting of the system’s function and decision making process.

Trust is inherently an abstract concept. Psychologically, it involves a willingness to be vulnerable based on positive expectations of another’s behavior [4]. These expectations stem from positive past experiences or, alternatively, the absence of negative ones. Therefore, it is essential to design systems that foster positive and reliable user experiences. However, since trust, by definition, requires vulnerability, there will always be an associated level of risk. This risk is inevitable, as there will always be a degree of uncertainty with system outcomes.

B. Explainable Statistics

In scenarios requiring rapid decision making and system reliability, understandable and intuitive statistics are essential for building trust and ensuring operational safety. In the scenario analyzed in this paper, where mission success and user safety are at risk, explainable statistics provide interpretable model outputs which support informed decision making and improve user understanding of system capabilities. One common statistical method used because of its interpretability and flexibility is linear regression. Linear regression models are built by identifying a response variable and a set of explanatory variables. The response is written as a function of the explanatory variables with each explanatory variable having an associated coefficient. Coefficients are estimated using the method of least squares and represent the marginal effect of a change in the associated explanatory variable on the response variable. The model also includes a random noise term which, for each sample in the data set, is independent of all other error terms and Gaussian distributed.

$$y = \beta_0 + \beta_1 x_1 + ... + \beta_k x_k + \epsilon$$

These models are transparent and clearly establish relationships between input variables and an output variable. Linear regression is also adaptable to a wide range of scenarios, allowing for the performance of transformations on both the response variable and the explanatory variables. For the purposes of this paper, linear regression was identified as an ideal tool for tying environmental metadata factors and conditions to the accuracy of mine identification systems. While other highly interpretable methods such as decision trees and naive Bayes classifiers could have been selected, the ease of performing marginal analysis from a linear regression model allows for rapid understanding of mission scenarios. Users can quickly check the influence of current mission conditions on the reliability of their mine detection and evaluation systems. Furthermore, decision makers are armed with information about the risks associated with following highly uncertain model outputs in critical operational situations. Incorporating linear regression models and explainable statistics more broadly ensures that decision makers can understand the rationale behind route recommendations and system outputs. If a system makes strong claims about what decision should be made but fails to provide interpretable outputs, users may not be aware of risks, threatening system trust. In the long run, leveraging intelligible system outputs improves user trust and builds an understanding of system limitations and risks.

C. Reinforcement Learning

Reinforcement learning (RL) is a type of machine learning algorithm underpinned by Markov Decision Processes (MDP) [5]. RL models are defined by several key attributes: an agent, an environment, policies, states, actions, rewards, and value functions. The agent performs actions within the environment, receives rewards or penalties based on specified conditions, and develops a policy to maximize cumulative rewards over a specified time horizon. The policy determines what action the agent will take in a state in order to maximize its reward. The goal is, over many iterations, to optimize the agent's policy, such that it can make effective, practical, and trustworthy decisions about future actions to be taken based only on its current state.

A MDP is defined by a tuple (S, A, P, r, β):

1) State Space (S): The set of all states in the environment.
2) Action Space (A): The set of all actions the agent can take.
3) Transition Probabilities $P(s'|s, a)$: The probability of transition from state s to state s' under action a.
4) Rewards $r(s, a, s')$: The reward after transition from state s to state s' under action a.
5) Discount Factor (β): A factor (0, 1) that discounts future rewards.

A policy is a rule that defines how a decision in each time period is chosen. A policy is a stationary policy if, for any state s, the policy chooses the same decision independent of the time period. A stationary policy is notated as δ and a decision for a particular state in that policy is denoted as $\delta(s)$ when the policy is stationary. The following approach can be used to find an optimal, stationary policy.

Let $\delta(s)$ represent an arbitrary policy and Δ represent the set of all policies. Then

- X_t = a random variable for the state of the MDP at the beginning of period t.
- X_1 = the given state of the process at the beginning of time period 1 (the initial state).
- d_t = the decision chosen during period t.
- $V_\delta(s)$ = the expected discounted reward earned during an infinite number of periods, given that at the beginning of the first period, the state is s and the stationary policy will be δ.

Then

$$V_\delta(s) = \mathbb{E}_\delta[\sum_{t=1}^{\infty} \beta^{t-1} r_{X_t d_t} | X_1 = s]$$

Where $\mathbb{E}_\delta[\sum_{t=1}^{\infty} \beta^{t-1} r_{X_t d_t} | X_1 = s]$ is the expected discounted reward earned during period t, given that at the beginning of period 1, the state is s and the stationary policy δ is followed. In a maximization problem, define

$$V(s) = \max_{\delta \in \Delta} V_\delta(s)$$

If a policy δ^* has the property that $\forall i \in S$

$$V(s) = V_\delta^*(s)$$

Then δ^* is an optimal policy.

There are a number of algorithmic methods for finding the optimal stationary policy for a MDP. Various RL methods use different approaches but, fundamentally, it focuses on determining an optimal policy, independent of time, that chooses decisions that maximize the cumulative reward received by the agent.

Reinforcement learning is ideal for modeling human control. It is flexible and adaptable to unforeseen circumstances, allowing for on-the-fly learning and long term policy improvements. The agent optimizes based on rewards discovered through trial and error. It learns the benefits of positive action choices and incurs penalties for suboptimal actions. This simulates the process that a human control agent would encounter. For both control systems, behavior is modified based on the feedback received by the agent with the goal of maximizing positive outcomes in the long run. An RL agent has the advantage of being able to optimize its long term policy over magnitudes more iterations in a given time frame than any human decision maker could. Assuming reward functions, action spaces, and state spaces are conscientiously defined with trustworthiness and reliability in mind, RL allows users to gain insights into mission strategies and operational risks more rapidly than alternative algorithms and control methods.

IV. Methods

A. Map Generation Design

The format of the example map provided a strong foundation for our initial design but led us to implement extensive modifications and extensions. At the core of this study is the concept of trust, a factor we felt the example did not fully represent. With prediction, such as the AI and human mine detection methods, there is an estimate and there is an accuracy. In this case, an estimate represents the belief of the system that a true positive or true negative condition is met. In the context of this problem, if there is a mine, we would expect the prediction method to estimate near 100% if it believes one is present, and near 0% if not. However, this is where the secondary aspect is crucial: accuracy. Accuracy is a latent variable representing the precision of the predictor. While an AI or human may have high confidence that a mine may or may not be present, the accuracy of the system is the difference between a false positive and a more catastrophic false negative. When accuracy is low, the belief of a predictor does not necessarily represent the truth. Accuracy, and knowing when a system is inaccurate, is critical in trust. Certain conditions, such as specific or novel metadata, will not always create a lower or higher estimate that a mine is present; however, the preconditioned training that the human and AI rely on to make a prediction may lead to entirely incorrect results. The central component of our simulation design is accuracy: the impact various metadata and environmental conditions have on the ability for a predictor to correctly make an assessment. With an underlying accuracy integrated, we are not simply dealing with the confidence of a predictive method as it relates to trust, but we are also exploring methods to counteract cases of low accuracy that undermine trust.

For us to create a measure of accuracy, a method was needed to relate metadata and environmental conditions to an impact on performance. To achieve this, we first needed to build an environment network. Due to the limited scope of provided metadata, we designed our own map generator to algorithmically build terrain and metadata. Our map generator is modular and expandable in a way that additional metadata can be removed or added from the base case. Relying on the example from the first phase, we integrated all available metadata such as: terrain, time, temperature, wind speed, visibility, and precipitation. In real world conditions, many of these variables are collinear and interdependent. To represent this, our generator relates factors such as visibility, wind speed, and temperature as dependent on other factors such as time, precipitation and terrain (see experimental design section for a full description for how these values are determined). All of these factors and their relationships are fully modifiable and can be conditioned to more extreme situations, representing novel or potentially specific environments if specific scenarios are desired across the whole map. Networks are fully customizable with the number of nodes, degree (how many connections), and the start and end locations accepted as parameters.

With the generated environment, the accuracy of our prediction methods can now be calculated. To perform this, we rely on logistic regression. Logistic regression was chosen because its response variable can be interpreted as a probability between 0 and 1. In this case, taking metadata and terrain into account as factors, we employ various linear and nonlinear combinations of the data to construct an accuracy metric, enabling us to assign the performance of the human and AI evaluation systems to the appropriate node. As creating an accuracy metric is not trivial, a literature review was conducted to explore how environmental conditions may impact the accuracy of UAV, human, and AI methods [6]–[10]. While these studies may not provide a full combination for the related impacts, the individual contributions were used to inform design and factor relationships. Accuracy was calculated for both the human and AI prediction method across the entire map, with several factors conditioned in favor of the human, for a more consistent accuracy across the environment.

As accuracy acts as only one of two components in prediction, a method of computing a belief estimate was needed. This method should take into account the accuracy of the system and if a mine was present, and then output a confidence estimate. When accuracy is low, the expected value of this estimate collapses around 50%, representing an equal likelihood of a high or low confidence of mine presence, regardless of the true state. As accuracy increases, the average estimate must converge to the true mine state. We explored several methods to accomplish these tasks, but yet again settled on a configurable logistic regression. Because logistic regression utilizes a logit function to map predicted values to probabilities between 0 and 1, it is ideal for binary classification problems, for example, where a mine is either present or not. Furthermore, a probabilistic belief estimate is well suited for capturing the uncertainty present in this mission context and the actual operational situations that users might face. This regression is able to be configured such that the rate and minimum accuracy of convergence is configurable. This means that the rate that the accuracy converges to the ground truth, and the minimum value at which this convergence starts, is able to be tuned to represent a more or less robust prediction method. For our estimate versus accuracy trade-offs for our two prediction methods, parameters were tuned for the human to be more robust in low accuracy conditions, and for the AI to have low predictive power with an accuracy below 60%. With the inclusion of an estimate, our map generator has created a configurable network with metadata, prediction estimates and accuracy for both the AI and human, and mines distributed across the map.

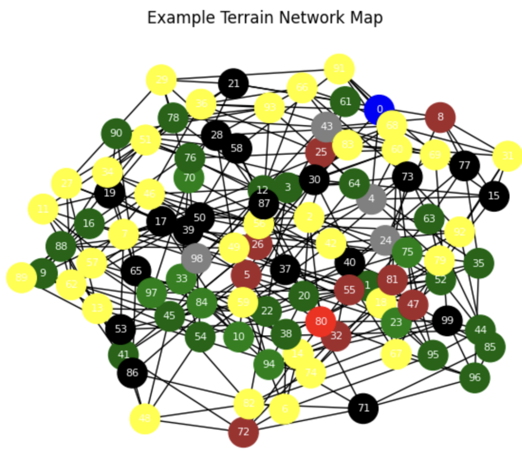

Fig. 4. Example Network Generation

B. Accuracy Methodology

The accuracy determination in our system utilizes logistic regression to model how environmental factors influence the reliability of both human and AI prediction methods. By incorporating metadata such as temperature, wind speed, visibility, precipitation, and terrain type, the model calculates an accuracy metric for each prediction. The logistic regression uses both linear and nonlinear transformations of these inputs to capture the effects of environmental conditions. For instance, visibility is scaled and transformed using a logistic function to simulate its non-linear impact on accuracy, with reduced accuracy in poor visibility conditions.

Temperature, wind speed, and precipitation are similarly scaled to reflect their respective ranges and impact on operational reliability. These effects are weighted by the visibility impact, as conditions like precipitation and wind speed often interact with visibility to amplify or mitigate their influence on accuracy. Terrain is factored into the model as a categorical variable, with different terrain types assigned specific weights based on their difficulty, such as grassy terrain being favorable and swampy terrain being challenging. As mentioned previously, literature was consulted to determine the appropriate method for developing these relationships mathematically.

The final accuracy metric is computed by combining these factors into a logit function, using predefined weights and an intercept to balance their contributions. A small amount of random noise is added to reflect real-world variability and uncertainty, and the result is clipped to ensure accuracy remains within a valid range between 0 and 1. This calculated accuracy serves as a critical factor for evaluating trust and guiding decision-making in the UAV and UGV operations.

C. Prediction Estimation

The method for generating prediction estimates is designed to translate the system's accuracy and the ground truth into a confidence score, or belief estimate, that reflects the likelihood of mine presence. This belief estimate adjusts dynamically with changes in accuracy, ensuring that the confidence score is meaningful regardless of the current accuracy level. The core logic employs a logistic regression framework with parameters tuned to reflect the desired trade-offs in prediction robustness for human and AI predictors.

The ground truth is encoded as +1 for mine presence and 0 for absence, forming the basis for determining the sign of the estimate. A threshold parameter (threshold) establishes a baseline below which accuracy is considered ineffective, with confidence estimates collapsing toward 50%. Above this threshold, the effective accuracy is scaled to range from 0 (at the threshold) to 1 (at perfect accuracy), allowing the system to adjust its sensitivity as accuracy improves.

The effective accuracy is then used to compute the mean (μ) of the logistic function's input distribution, scaled by a tunable parameter kappa, which controls the strength of the estimate's dependence on accuracy. Variance (σ^2) is scaled inversely with effective accuracy, ensuring higher variability in predictions when accuracy is low and greater confidence when accuracy is high. A random noise term, drawn from a normal distribution parameterized by this variance, introduces stochasticity into the estimate to reflect real-world uncertainties. Finally, the estimate (L) is passed through a sigmoid function to produce a probability-like output ranging between 0 and 1, representing the system's confidence that a mine is present. This confidence estimate is robustly configurable, with kappa, threshold, and noise scale parameters allowing the model to adapt to specific requirements. In the case of our simulation, we conditioned these parameters to allow for a strong predictive power even in lower accuracy instances for the human, and a stricter requirement for the AI at accuracy <60%.

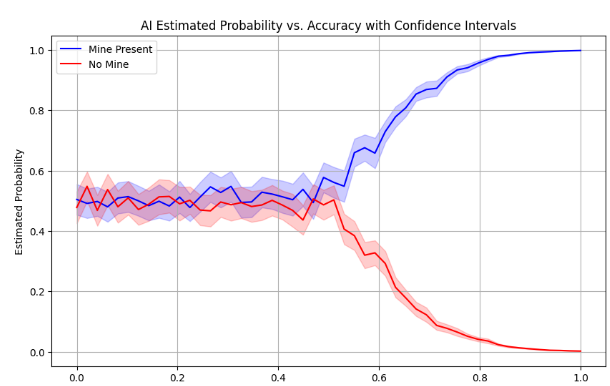

Fig. 5. AI Estimated Probability vs. Accuracy with Confidence Intervals

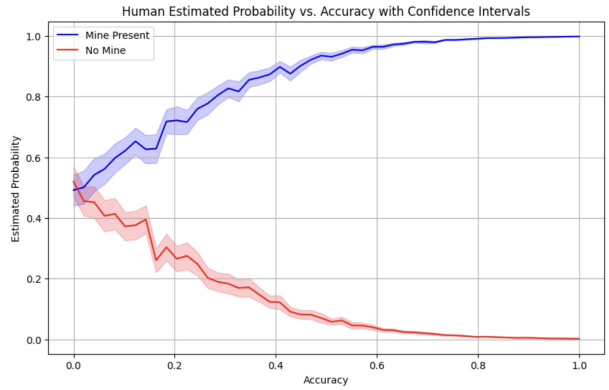

Fig. 6. Human Estimated Probability vs. Accuracy with Confidence Intervals

D. Simulation Design

In approaching simulation design, we chose to use the provided simulation as a core framework, but with external modifications in the form of a mission wrapper. The mission wrapper is designed in a modular way to extend on functionality within the base mission class, providing helper functions, streamlining certain processes, and integrating an optional parallel time processing class to allow for events to occur simultaneously. With our more complex map generation, a single line of code is required to handle compatibility with the example terrain design, and our new version. The greatest distinction between our mission wrapper and the base class is the way in which events are handled. Opposed to being a continuous stream at which functions can be called, our simulation is discretized in the form of a MDP. In the context of our minefield traversal problem, the MDP consists of a set of states representing information about the current environment: specific locations on the map around the UAV and UGV with their associated metadata, a set of actions available to the agents: scan or move, and a reward function that guides the agents toward optimal decision making. MDP is step-based, meaning for each iteration of the simulation an action is passed, a single move of the UAV for example, and the current state will be updated with a reward returned based on the advantage of the move. The next step occurs with the process repeating until a terminal state is reached.

Within our mission wrapper, the action is an array of size N * 4, where N represents the maximum degree of all nodes in the map. The first N indices represent moving the UAV, the second N are move and scan with AI, the third N are move and scan with the human, and the final N move the UGV.

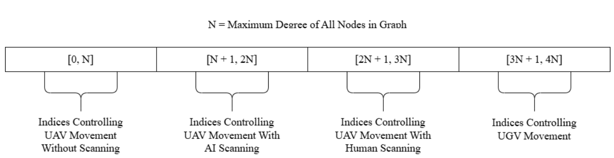

Fig. 7. Illustration of Agent's Action Array

For each iteration of the mission wrapper, a base state is returned with environmental data surrounding the UAV and UGV containing:

1) The surrounding cells metadata
2) AI scan status: cells that have been scanned by the AI
3) Human scan status: cells that have been scanned by the human
4) Traversal status: whether the cell has been visited by the UAV or UGV
5) Directional information for the UAV and UGV: an array with the node in the direction of the goal highlighted
6) Distance of the UAV from the goal
7) Distance of the UGV from the goal
8) Distance between the UAV and UGV

As an additional aspect, metadata and scan status radius can be increased with a Depth parameter within the mission wrapper allowing for the information to contain cells in layers beyond the immediate neighbors. All state information is configurable within the mission wrapper class, and can be modified for specific use cases. Although there is a constraint with how the original terrain generation occurred, all back end information such as accuracy, mine location, and unscanned AI and human estimates are protected from being directly accessed by the mission wrapper class.

E. Simulation Setup and Base Parameters

There are several configurable aspects within the map generation, accuracy determination, estimate derivation, and simulation. This section will discuss the base parameters.

1) Terrain transition matrix: this provides a matrix representing the likelihood of transitioning from one terrain type to the next, or ending up in the same terrain. Due to similar terrains occurring in proximity to another, this parameter allows for larger blocks of a particular terrain type to be generated in the map. Most values are positioned in a way that a repeat in the terrain type is most likely. There are also cases, as with desert and swampy, where no transition is possible (an intermediate is required)
2) Precipitation params: This parameter is for precipitation likelihood and amount, relying on sampling from an exponential distribution for values at each cell.
3) Temp params: Several factors are involved with this including base temp, diurnal variation, and precipitation effect. Base temp gives the average temperature of the cell, diurnal variation incorporates time and the effect the day night cycle has on temperature, and precipitation is a discount factor lowering temperature with greater rain amounts.
4) Wind params: This parameter is very similar to temperature but deals with time versus diurnal variation.
5) Visibility params: Visibility is unique for each terrain type with a maximum, based on factors like tree cover etc. Additionally, by time (whether day or night) and precipitation greatly reducing visibility.

V. Designing a Trustworthy Intelligent Agent

A. UGV Routing

In this challenge there exists two semi-dependent control problems. Routing the UAV is based on determining which cells to scan – and by what method – to provide the UGV the highest confidence route in reaching the goal. The UGV must rely on the ability of the UAV to scan cells to determine a route with the lowest likelihood of encountering a mine. To simplify the complexity of the overall system, we considered the control of the UAV to be our primary objective. In the event the UAV is successful in scanning cells on a route to the goal, and scans enough cells that a path without mines can be confidently found, the control of the UGV is achieved through cost-based routing. Cost-based routing is a form of algorithmic pathfinding in which the distance, or cost, of navigating a particular path is minimized; i.e. the shortest path can be found based on a cost constraint. The first aspect of our approach was implementing cost-based pathfinding to control our UGV agent within the mission environment. To achieve this we relied on the A* pathfinding algorithm for its efficiency and low computational complexity. The A* algorithm calculates a total cost for each potential path, incorporating both travel cost and a metric called heuristic cost. The travel cost, g(n), represents the cumulative effort of moving from the start node to the current node, considering factors like physical distance and terrain difficulty. The heuristic cost, h(n), estimates the remaining cost to the goal, for which we used a Manhattan distance heuristic due to the network structure of our environment. To incorporate an understanding of uncertainty and mine presence, we integrated mine probability data into the cost function. Initially, unscanned cells are assigned a high cost of 100, reflecting uncertainty and potential danger. As the UAV scans cells, this uncertainty is reduced and the cost is adjusted based on the probability estimate of a mine. Cells with a high likelihood of containing a mine remain costly, but their cost is still lower than the initial value due to the added confidence provided by the scan. This adaptive approach encourages the UGV to avoid high-risk areas while finding the lowest-cost route to the goal. The system is designed to dynamically recalculate the UGV's path with each step as new data from the UAV becomes available. Whenever scan results significantly alter the probability estimates for cells along the planned route, the A* algorithm is re-run to ensure the UGV's path remains both safe and efficient. This routing method allows for efficient time utilization and ensures that the UGV remains fully operational throughout the duration of the simulation, maximizing its contribution to mission success.

B. UAV design

Control of the UAV is divided into three key components: determining where to navigate, identifying which cells to scan, and deciding the method of scanning. While heuristic or algorithmic solutions could achieve these objectives, we opted to utilize reinforcement learning (RL) due to its adaptability and potential for optimizing complex control problems. RL, a subset of machine learning, operates on the principle of learning through interaction with an environment to maximize a reward. By defining a clear reward structure—positive reinforcement for successful actions and penalties for failures—an RL agent can iteratively improve its performance through trial and error. The decision to use RL offers significant advantages in terms of flexibility and transparency. The reward framework serves as a generalized ruleset that aligns the behavior of the UAV with mission objectives, such as prioritizing high-impact scans or minimizing redundant movement. Moreover, the iterative nature of RL allows the agent to adapt to novel scenarios and environmental changes without requiring extensive reprogramming. The transparency of RL is another critical benefit, as the agent's behavior is directly tied to the defined reward system. This ensures that the decision-making process is interpretable and can be adjusted as needed to reflect changing priorities or mission goals.

For this study, we employ an RL agent that uses a multilayer perceptron (MLP) neural network as its policy network architecture. Training is implemented using the proximal policy optimization (PPO) algorithm. A flattened vector representing information about the current state is input into the MLP network which outputs action probabilities. This approximates a policy for the agent. MLP is an ideal network architecture for this use case due to its ability to handle discrete action spaces, process high-dimensional data, and scale to larger minefield networks. PPO uses a clipped surrogate objective function to optimize the actions taken by the agent and, thus, its policy. The algorithm tunes the parameters of the MLP network, improving the agent's performance and guiding it towards an optimal, stationary policy. As an on-policy method, PPO ensures that the agent only learns from actions taken by its current policy. This method limits the influence of outdated policies, supporting efficiency and stability in training.

Within the framework of our mission wrapper simulation, the RL agent takes in state information, and outputs a control action for the UAV. As the UGV is a dependent policy, the reward will be independent of UGV performance with the exception of mine encounters, which indicate a failure in the ability of the UAV to effectively guide the UGV along a safe path. This design ensures that the control policy is primarily evaluated on its own performance metrics, such as scanning accuracy, efficient navigation, and the ability to reduce uncertainty in the environment. While the actions of the UGV are influenced by the UAV, the reward structure isolates the responsibility of the UAV in creating a safe and high-confidence route, thereby disentangling the two agents' contributions to mission success.

C. Explainable Statistics

With trust being the key focus of this study, a method is needed to provide verifiability and transparency to decision making. To achieve this, we rely on using explainable statistical models for accuracy verification. To reiterate, in a prediction there is the estimate (the confidence of the model there is a positive), and there is the accuracy of the predictor (the ability to successfully make an estimate). With accuracy being a latent variable not accessible by the UAV, UGV, or a human monitor, we designed a system that leverages explainable statistical models in the form of linear regressors to infer and verify accuracy based on observable environmental metadata and prediction estimates. These models are critical in ensuring that decision-making processes are transparent and interpretable, fostering trust in the system's ability to operate autonomously in high-stakes scenarios. By analyzing the relationships between metadata factors—such as terrain type, weather conditions, and visibility—and the prediction outcomes, we are able to estimate the confidence of the predictor in detecting a mine, or not, across all available cells. In cells with low predictive power, a cell in which a positive mine estimated 50% confidence, for example, we can infer accuracy to be low and that the cell should be avoided. Linear regression was selected for its simple interpretation and ability to rapidly convey information to agents about the relationships between input variables and the model output. The choice of linear regression is more thoroughly supported in Section III.

To train the linear regression model, we interacted with the simulation to extract metadata, human and AI estimates, and the ground truth of whether a mine was present. Using this data, a simple linear regression model was trained with metadata factors and mine presence as predictors to estimate the human and AI's confidence regarding the presence of a mine. Although in practice it is not possible to know beforehand whether a mine is present, this training approach allowed us to manually fix the mine presence variable during simulation to calculate the corresponding confidence estimates under known conditions. When accuracy is low, the model reflects this by estimating values closer to 50%, indicating uncertainty regardless of whether a mine is present or not. Conversely, in conditions of high accuracy, the model demonstrates stronger predictive power, with estimates diverging significantly from 50% based on the ground truth. This approach leverages the regression model to infer accuracy metrics indirectly, bypassing the need for direct access to the underlying conditions during real-world application. By employing regression, we can dynamically adapt the accuracy estimates to environmental factors and scanning outcomes, ensuring the system remains both robust and interpretable.

With an accuracy metric established, we rely on these predicted values in place of environmental metadata as inputs into the RL model. This decision was driven by two key considerations: explainability and adaptability. From an explainability perspective, this approach makes it easier for a human operator to audit the RL agent's actions. By focusing on expected accuracy as the basis for decision-making, it becomes clear why the agent might choose to navigate or avoid a particular cell, enhancing transparency in its behavior. The adaptability advantage lies in the flexibility of the system's data requirements. If specific metadata or environmental conditions become unavailable, a new linear regression model can be quickly trained to generate the necessary accuracy estimates. This eliminates the need for time-consuming retraining of the RL model, ensuring the system can adjust rapidly to changes while maintaining performance.

D. Risk Based Monitoring

To ensure the trustworthiness of the system, effective risk monitoring and validation mechanisms must be implemented, particularly in evaluating the navigation decisions of the UAV and UGV and the associated confidence in their predictive accuracy. Our approach emphasizes creating interpretable metrics that assess the agents movements in relation to regression outputs and their ability to avoid high risk areas where prediction accuracy is low.

The UAV's decision-making process relies heavily on regression models that estimate the accuracy of mine detection based on environmental metadata. These estimates provide a probabilistic confidence metric, with low values indicating high uncertainty or a higher likelihood of incorrect predictions. To monitor risk effectively, we track the UAV's movement patterns in relation to cells with low predictive accuracy and flag instances where the UAV prioritizes such areas without a compelling reason, such as lack of alternative paths or operational constraints. Metrics such as the Accuracy Avoidance Ratio (AAR) are established to quantify the percentage of UAV navigation steps directed toward cells with accuracy below a defined threshold. The Accuracy Avoidance Ratio (AAR) is defined as:

$$\text{AAR} = \frac{\text{Number of moves to low-accuracy cells}}{\text{Total UAV moves}} \times 100$$

Where:

- *Number of moves to low-accuracy cells*: The total number of UAV navigation steps directed to cells with accuracy below a predefined threshold.
- *Total UAV moves*: The total number of navigation actions performed by the UAV.

A higher ratio may indicate poor decision-making, whereas a low ratio reflects effective avoidance of high-risk areas.

For the UGV decision making, we utilize Surrounding Scan Confidence (SSC) which measures the proportion of surrounding cells within a defined radius of the UGV that have been scanned by the AI or human, weighted by their respective accuracy. Higher values indicate greater confidence in the UGV's immediate surroundings.

The Surrounding Scan Confidence (SSC) is defined as:

$$\text{SSC} = \frac{\sum_{i=1}^{N} \text{Accuracy of scanned cell}_i}{N}$$

Where:

- N: The total number of cells within a defined radius of the UGV.
- *Accuracy of scanned cell$_i$*: The confidence value (accuracy) of the i^{th} cell, derived from regression models or prediction outputs.

These metrics provide a framework for risk monitoring across both agents. For the UAV, navigation decisions are validated against regression outputs, ensuring it prioritizes areas that improve prediction accuracy and avoid unnecessary risks. For the UGV, metrics focus on the extent and quality of scanning conducted by the UAV, directly linking the UAV's scanning behavior to the confidence in UGV traversal.

By tying navigation decisions to these metrics, we create a transparent and explainable risk monitoring system. This not only validates the trustworthiness of the UAV and UGV but also provides actionable insights for refining their behavior to enhance safety and mission success. This integrated approach ensures that the system operates reliably even under high levels of uncertainty.

VI. Experimental Design and Results

With our simulation, approach, and methods determined we can now begin experimentation. Within our framework there are several aspects we evaluate regarding RL and simulation parameters. Our primary focus was on the design and evaluation of the RL agent's reward function, which plays a critical role in directing the agent's behavior. The reward function was designed to balance multiple objectives, encouraging behaviors that align with mission goals while discouraging inefficient or detrimental actions. Specifically, the reward structure includes the following components:

1) Distance to Goal: A positive reward proportional to the reduction in the distance between the UGV and the goal is applied. As the distance between the UGV and the goal factors into account the cost of the cell, and reduction that occurs from scanning, the distance decreasing represents a valid scan and low likelihood of mine occurrence. This incentivizes the UAV to guide the UGV closer to its target while avoiding high uncertainty locations.
2) Scans Performed: Rewards are assigned based on the proportion of AI and human scans conducted surrounding the UGV neighbor cells. This encourages the UAV to optimize its scanning strategy, prioritizing areas surrounding the UGV to reduce uncertainty and improve confidence in the UGV's route.
3) Mine Encounters: A significant negative reward (-500) is assigned when the UGV traverses a cell containing a mine. This heavily penalizes actions that lead to mission-critical failures, reinforcing the importance of accurate scanning and effective guidance.
4) Action Efficiency: A penalty is applied to inefficient or redundant actions. This discourages invalid actions with more than a single value occurring in the action array.
5) These components are combined with adjustable multipliers for distance, scans, mine encounters, and action efficiency. This flexibility allows us to tune the reward function for specific scenarios or priorities. For example, in scenarios where the UGV's mine removal capabilities are not 100% effective, the multiplier for mine encounters can be increased to emphasize risk aversion.

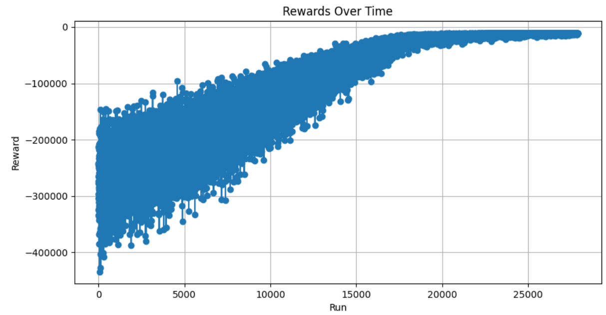

Fig. 8. Intelligent Agent Rewards Over Time

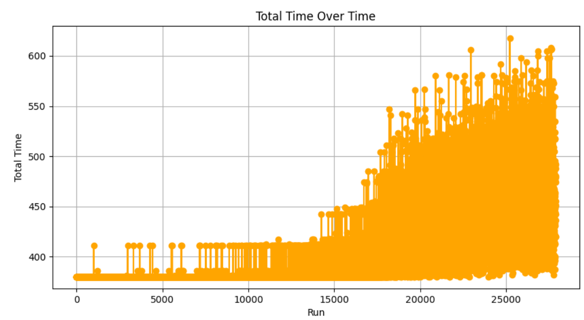

Fig. 9. Intelligent Agent Time Cost Over Training

Our evaluation of the reinforcement learning (RL) agent focused on the effectiveness of the reward function in guiding the agent's behavior within the simulation. The results, as illustrated in Figure 8, demonstrate a significant increase in cumulative rewards over time, converging to approximately -2000. This trend indicates that the agent is adapting to the defined incentives, albeit with some limitations observed in the initial training phase.

The rewards are initially heavily negative, primarily due to the penalty applied for invalid actions, which occurs when the action array contains more than one active value. The reward function strongly disincentivizes these invalid actions, as the simulation executes the action with the lowest index when multiple values are passed. Given that the first N indices of the action array correspond to "move the UAV without scanning," the agent's inability to associate scanning with additional rewards is evident in the early training steps. As training progresses, the agent begins to adjust its behavior to optimize rewards, leading to the observed convergence. However, this convergence is still suboptimal, likely due to insufficient association between scanning and reward gains within the current training duration. The time usage results, shown in Figure 9, reveal that the agent executes actions with time costs, indicating a trade-off between reducing time costs and minimizing mine encounters. While reducing time costs is a priority, this penalty is an acceptable compromise when it results in improved safety through mine avoidance. The observed execution of time-costly actions suggests that the agent recognizes the necessity of these actions in addressing mission-critical objectives. However, the balance between time efficiency and mine avoidance requires further refinement in both the reward function and the agent's policy.

We show no quantitative results for reducing mine encounters, as within the limited training duration, we were unable to reduce the incident rate. Over additional timesteps and tuning of the reward function, we are confident that our approach is sound and that the agent will learn to decrease the number of mines encountered. This will be a key focus of future work.

Despite the limited scope of results, this experiment establishes a foundation for future exploration, providing insights into the relationship between reward function design and RL agent behavior within the constraints of our simulation framework.

VII. Discussion

A. Relevance of this Work

This research addresses the critical challenge of embedding trust and accountability within the adoption and integration of AI systems, an issue magnified by the rapid development of AI technologies and their growing influence on daily life. Through a novel approach, we developed a unique simulation environment that includes a mission wrapper for parameters such as starting and goal nodes, a list of scanned and traversed edges, a network graph generated from a list of provided edges with specified metadata factors, a black box style framework to facilitate reinforcement learning, and a continuously tracked distance between the UGV and its goal, significantly enhancing the modularity of the original setup. Environment metadata and its relationship to underlying human/AI accuracies followed best practices for AI by using explainable statistics from cited literature reviews to verify decision making and assumptions overall explaining the features behind the black box simulation.

To navigate this simulation, an intelligent agent was created to act as a routing system for warfighters, UGVs, and UAVs, leveraging a custom reward system to optimize reinforcement learning for minefield traversal. This research contributes to the understanding of the interplay between trust and AI systems, offering insights valuable to government officials, military personnel, warfighters, and the general public. The findings have far-reaching implications for national security, human life, and mission success, emphasizing the necessity of developing robust and efficient AI systems that inspire user trust.

Beyond its immediate applications, this research adds to the broader discourse on the ethics of mission success, particularly in weighing the trade-offs between minimizing casualties and optimizing mission speed. Future research will expand the simulation environment and refine the intelligent agent, ensuring alignment with DEVCOM's values and the development of trustworthy systems. This study underscores the critical importance of simultaneously building robust system models and fostering trust in those systems, as both are indispensable for ensuring their efficient and effective use.

B. Future Work

The system design is expected to evolve substantially in the final phase of the project. One key enhancement involves parameterizing the simulation to allow for greater customization and the creation of unforeseen circumstances for the intelligent agent. This will enable testing under a wider range of scenarios, improving the system's adaptability and robustness.

In future stages, the reliability of individual subsystems within the overarching system may not be guaranteed. For example, UGVs may not consistently disarm mines, or UAVs may face constraints such as limited battery life. The addition of new subsystems or replicated subsystems, such as additional UGVs or UAVs, is also anticipated. To address these complexities, the simulation has been designed with a high degree of modularity, incorporating parameters that can be adjusted to reflect competition specifications and real-world conditions. Current adjustable parameters include the number of nodes, UAV and UGV depths, the number of edges, underlying human and AI accuracy in diverse environments, predictions and outcomes for mine encounters, traversal times, subsystem statuses and locations, and metadata related to environmental interactions. Planned extensions include adding parameters for the number of UAVs and UGVs, further enhancing the simulation's flexibility.

The project's objective metrics remain a key focus of ongoing work. They allow for unbiased evaluation of the systems ability to incorporate trust and reliability, the overall goal of this exercise. Metrics under active exploration include minimizing human loss and injury, optimizing the UGV/UAV's ability to maximize cumulative rewards, and improving the time percentage of AI and human utilization to optimize both time efficiency and accuracy. Continued experimentation with the intelligent agent is expected to improve metric performance, resulting in a more accurate and precise system capable of supporting complex mission requirements.

Another critical area of future work involves conducting an expanded literature review with a focus on the trade-off between time costs and human safety, particularly the preservation of warfighter lives. This will become increasingly significant as the potential for unreliable UGV systems introduces heightened risks to human operators. If UGVs fail to perform consistently and human lives are placed at greater risk, the balance between operational efficiency and the mitigation of injury or death will demand even greater scrutiny. Optimal strategies for minefield traversal which, in the current state, do not consider the risk of UGV failure, will change. With a heightened emphasis placed on life preservation, there may be an increase in time costs, threatening successful mission outcomes. Potential changes to RL methods and environmental considerations underscore the need for a deeper exploration of ethical and practical considerations surrounding these trade-offs, building on the foundational materials already reviewed.

Overall, these future directions aim to ensure that the system not only achieves technical reliability but also aligns with the ethical and operational priorities of mission success, trustworthiness, and human safety.

C. Key Workforce Skills and Abilities

The successful deployment and operation of an AI-enabled minefield navigation system requires a multidisciplinary skill set encompassing technical expertise, operational proficiency, and human-AI collaboration abilities. Established roles, such as human subject matter experts (SMEs) for analyzing UAV imagery, UAV and UGV technicians and operators, ground troops, and engineers for ongoing system development, remain essential for ensuring system reliability during high-stakes operations. These personnel must be adept at mission planning, troubleshooting, and risk assessment, as well as responding to unpredictable conditions, including subsystem failures or environmental changes.

In addition to these foundational roles, the integration of AI introduces new workforce requirements. These include AI IT technicians responsible for handling bug fixes and model adjustments, AI software engineers tasked with creating and integrating new functionalities, and personnel with general knowledge of the system to facilitate cohesive collaboration across all mission roles. Engineers with experience in machine learning, statistical modeling, system architecture, and experimental design are needed to replicate work similar to that performed in this study. They will require access to systems engineering software, an array of programming tools, and substantial computing power. Furthermore, the increasing reliance on AI systems demands a dedicated cyber workforce to actively defend the system against intrusions, employing key cybersecurity infrastructure such as firewalls, virtual private networks (VPNs), and secure local networks. This cyber team ensures the system remains secure from adversarial attacks, safeguarding operational integrity and mission success.

Building trust in AI systems is a critical aspect of workforce readiness. Operators must be able to interpret AI recommendations, assess their validity, and integrate them with human judgment to ensure safe and effective navigation. Trust in the system must be cultivated through intensive testing and simulation modeling, demonstrating the system's reliability and performance in various high-stakes scenarios. This process will be supported by a systems engineering risk management workforce, which will monitor, analyze, and mitigate risks or failures, fostering confidence in the AI system's ability to perform effectively and safely under diverse conditions.

This research highlights the importance of aligning workforce skills with the growing role of AI in defense and security. By identifying these critical competencies, this study provides a foundation for designing training programs and operational frameworks that ensure personnel are equipped to leverage advanced technologies while maintaining trust and accountability. Preparing the workforce with these skills is essential to maximize the potential of AI-enabled systems and ensure their safe, effective, and ethical deployment in high-stakes scenarios.

D. Adoption in the Workplace

To enable others to replicate and build upon the findings presented in this study, a systems engineering approach was adopted to ensure clarity, modularity, and adaptability. Specifically, a top-down methodology was employed to evaluate the problem comprehensively and design the necessary tools for research and development. This approach ensured that the project scope was sufficiently broad, considering all potential factors influencing the problem before developing solutions, while maintaining a structured and systematic process.

The systems engineering methodology is detailed in earlier sections of this paper, starting with the mission process flows, objectives, and metrics discussions. Visual aids, such as objective trees and process flow diagrams, are provided to clarify the problem-solving approach and enhance understanding for readers. These tools serve to both communicate the rationale behind design choices and provide a template for future research. The technical components, including coding processes and the overall code framework, are outlined to offer a structured way for other researchers to replicate the work or approach the problem from a similar perspective. This structured framework enables validation of the current findings while also providing a foundation for exploring novel solutions.

The adaptability and scalability of the system are key features that facilitate adoption. The system's flexible architecture enables adaptation to scenarios beyond minefield navigation, including disaster response or autonomous logistics. For example, the modular design of the simulation and intelligent agent allows researchers to customize the system by adding or removing parameters, such as environmental metadata, traversal rules, or new operational goals, to suit diverse applications. Furthermore, the black box design of the intelligent agent facilitates seamless integration with reinforcement learning platforms, enabling researchers to apply alternative training methodologies or tailor the agent to new domains with minimal system disruption.

E. Conclusions

The broader impact of adopting this work has significant implications for the armaments systems engineering industry. By leveraging this system, researchers and practitioners can accelerate the development of assured AI systems in high-risk environments, fostering safer and more efficient operations. The adaptability and robustness of the methodology contributes to advancements in areas such as national security, autonomous navigation, and human-AI collaboration. Additionally, the modular design encourages collaboration, enabling teams to refine and expand upon the system while addressing emerging challenges in AI reliability and trustworthiness.

Finally, the study's discussion of future directions serves as a road map for subsequent researchers. They are encouraged to replicate the results by following the outlined methodology or to innovate by pursuing new approaches that build upon this work. By providing a robust, adaptable framework and a clear research trajectory, this study ensures that its contributions can be readily adopted and expanded, fostering continued progress in the development of trustworthy AI systems for complex, high-stakes applications.

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