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Artificial Intelligence for Air Defense Assets

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Author Note: With Lockheed Martin as project sponsors, the authors conducted a year-long senior research project at the United States Military Academy in the Department of Systems Engineering under the advisement of Raymond Vetter. Raymond Vetter is a Major in the United States Army and serves as an assistant professor in the Department of Systems Engineering.

Abstract: The future of air and missile defense increases in complexity with the advancement of hypersonic missiles. Technological enhancements are critical to mitigate the high-risk outcomes of these threats. As artificial intelligence's recognition, potential, and use-case rise, it is critical in determining how to utilize such technology for air and missile defense. The purpose of this study is to determine artificial intelligence's benefit within the air and missile defense and the Find, Fix, Track, Target, Engage and Assess kill chain (F2T2EA), which encompasses the sequence of events from missile launch to target hit. By utilizing the Systems Decision Process, the research followed a four-phase process to gather the recommended solution: defining the problem through stakeholder analysis and value modeling, generating appropriate candidate solutions, making a recommendation, and developing an implementation plan. The team assessed how AI, shot doctrine, and radar capabilities impacted total system value. This total system value was compared to cost to assist the team to make a final recommendation on which alternative is most beneficial.

Keywords: Air and Missile Defense, Artificial Intelligence, F2T2EA Kill Chain, Systems Decision Process

1. Introduction

Artificial intelligence's (AI) use cases and future potential are constantly advancing. Given the complex nature of hypersonic missiles, implementing technology aimed at mitigating potential threats is crucial. The future of air and missile defense (AMD) relies on the integration of AI to combat hypersonic capabilities. As the multi-domain battlefield is changing, technologies must adapt respectively; therefore, the nation's defense contractors are working to equip missile systems with these enhancements to ensure success in the future of warfare.

The 2021 National Defense Authorization Act highlights the rapid advancement of hypersonic vehicles and Intermediate-Range Ballistic Missiles (IRBMs) (116th Congress, 2021). Lockheed Martin is primarily focused on developing a system that integrates AI to combat any incoming missile threats, especially hypersonic missiles. The high speeds and maneuverability make it critical to predict and detect the paths of these threats. Missiles that can perform angled maneuvers are a threat that demand a dynamic solution. AI presents a solution that can rapidly adapt, allowing for dynamic path prediction. This project delivers and recommends a course of action to mitigate these ballistic and hypersonic threats.

To develop recommendations for the integration of AI into AMD, the team used the Systems Decision Process (SDP). This process involves four stages: problem definition, solution design, decision making, and solution implementation (Parnell 280-281). Before conducting an in-person stakeholder analysis with the clients at Lockheed Martin, the team developed a problem statement and built a value hierarchy to refine and model the project's goals to meet the needs of the client.

A value model was designed to create a qualitative scoring method to rank each of the system's attributes. Additionally, Lockheed Martin's proprietary simulation software, SmartSet, ran specific scenario simulations and provided a baseline model to generate value measures and determine which measure would have the highest impact on the performance of the overall system (Warnke, 2021). After reviewing similar research, various AI software and algorithms such as SoPhie and DeepGlo were concluded to potentially improve performance in terms of detecting the predicted path of incoming missiles. These capabilities are advantageous to the missile systems.

2. Methodology

The team used a decision-making framework developed by the Department of Systems Engineering at the United States Military Academy: the SDP. Value focused thinking provides the basis for the SDP; therefore, the team developed alternatives after the identification of stakeholder preferences. Starting with problem definition, Lockheed Martin's feedback and issues helped to determine specific needs and goals through value modeling and stakeholder analysis. Next, alternative generation and cost analysis allowed for solution design and the decision recommendation based on value scoring and simulation analysis. After data revision and review, the team generated the recommended solution utilizing solution value scoring and cost estimates.

2.1 Problem Definition

The problem definition stage of the SDP, the red circle of Figure 1, frames the rest of the project. During stakeholder interviews, Lockheed Martin and current Air Defense Artillery operators helped establish the intent in the overall process of missile defense and design. Through the research done by the team and the information gained from meetings and interviews, the team determined that the most efficient way to model the problem was through the Find, Fix, Track, Target, Engage and Assess kill chain (F2T2EA), shown in Figure 2. The kill chain represents a thorough, six-step process of a missile defense system against an incoming threat beginning with finding a target and ending with assessing the success of the engagement.

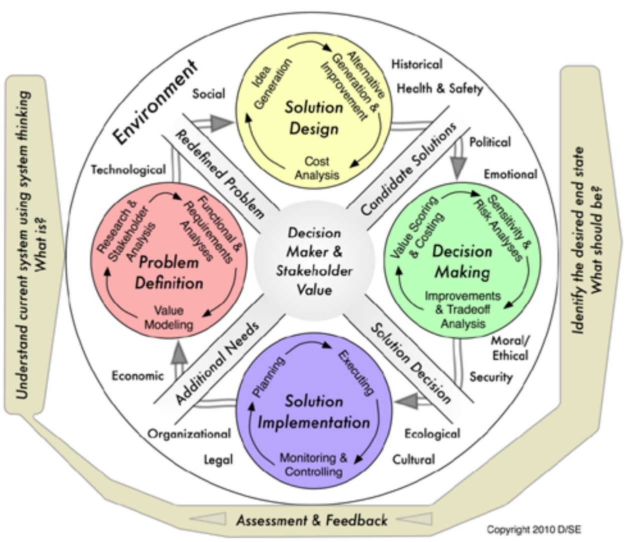

Figure 1. Systems Decisions Process (SDP) (Parnell, 2010, p. 17)

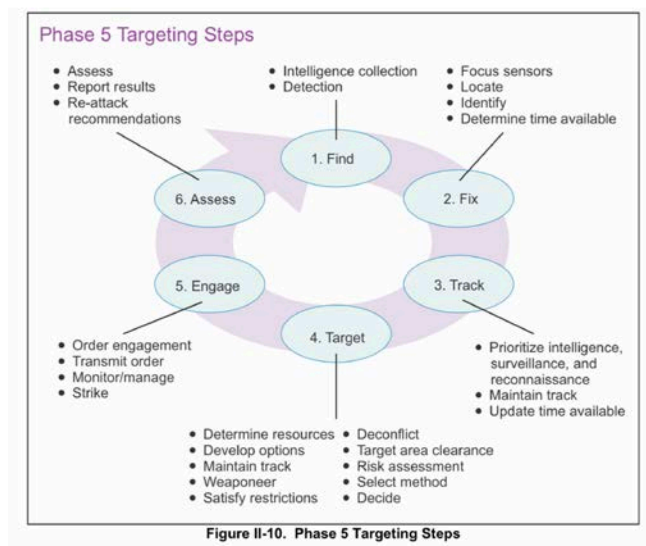

Figure 2. Kill Chain F2T2EA (Department of Defense, 2013)

The value hierarchy shown in Figure 3 served as a starting point with the fundamental objective, "To Defend and Protect Friendly AO from Enemy Intermediate Range Ballistic Missiles (IRBM) and Maneuvering Hypersonic Missiles," and value functions from the different stages of the kill chain. As the team's research continued, the value model was modified to contain six value measures based upon stakeholder analysis. The value measures were then assigned swing weights based on variation and importance. The swing weight matrix enables the team to highlight the most influential value measures. Concurrently with the swing weight matrix development, the team assigned each value measure a value function ranging from 0 to 100 based on the raw data. This allowed for a transition to scoring each alternative against one another based on the values and scores that the team found through research done in the Problem Definition phase of the project. Using the swing weights and value functions, an additive value model allowed for alternatives to be compared on a 0 to 100 scale factoring in key metrics.

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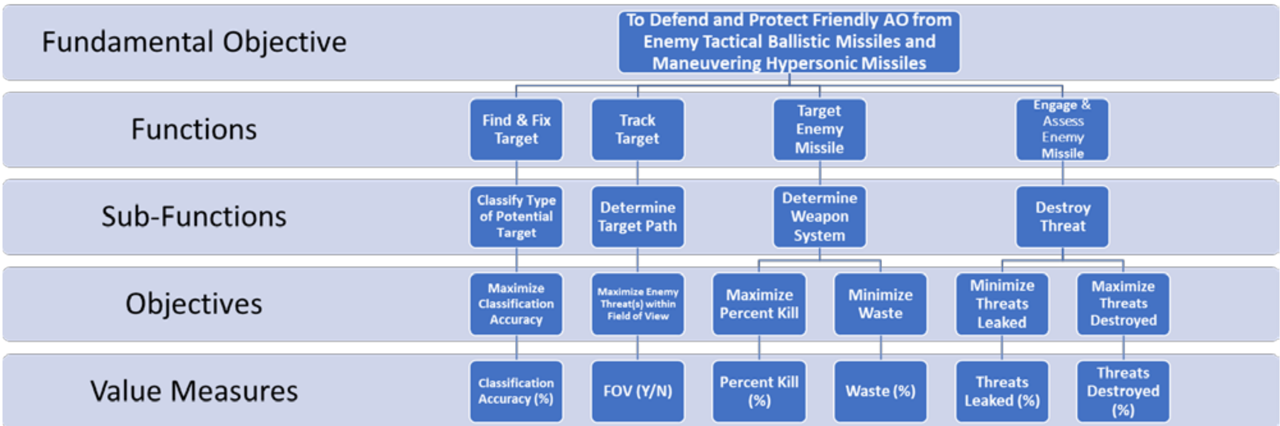

Figure 3. Value Hierarchy

2.2. Solution Design

The second phase of the SDP focuses on solution design. This phase involves alternative generation and produces feasible candidate solutions. To develop a realistic scenario, the team coordinated with a Lockheed Martin simulation expert, Mr. John Warnke, to develop the baseline shown in Table 1. Building off the baseline simulation the team incorporated elements of AI research in addition to alternatives that represent potential improvements to the system. Within Table 1, Terminal High Altitude Area Defense (THAAD), Aegis, and Patriot refer to the missile defense systems analyzed which are, respectively, the THAAD, the Aegis Combat System, and the Patriot Advanced Capability – 3 (PAC-3).

Working with Mr. Warnke to determine the inputs for the SmartSet program, the following variables were able to be altered to represent inputs for each alternative. The inputs in each alternative are Field Of View (FOV), AI implementation, and shot doctrine. PK represents percent kill determining the defense system's percent of enemy targets destroyed. The shot doctrine displayed as "Shot #," represents the standard operating procedures for each missile system where S stands for shoot, L for look, and C for classify. For example, if an incoming threat is detected and the shot doctrine is SLS the system will fire one interceptor and then look to see if has destroyed the interceptor. If it did not destroy the threat, then it would fire another. Similarly, if the doctrine includes classification, the system determines the type of threat (Hypersonic, IRBM, etc.) before firing. The FOV, range, and altitude shows the angular field of vision, distance, and altitude capabilities, respectively.

The team initially developed 26 different alternatives, each altering the corresponding attributes. After initial analysis, the team deemed the 26 alternatives developed were best represented by the alternatives in Table 1. The team's analysis that allowed for the alternatives below can be found in Section 3, Results. The team derived the values for the inputs "Shot Doctrine" and "Percent Kill" from Lockheed Martin's input and further research into both SoPhie and DeepGlo. The last five alternatives in Table 1, depict combination alternatives that can integrate various AI capabilities, shot doctrine, and radar technology.

Table 1. Simulation Inputs

Alternative	**Aegis PK**	**Aegis Shot #**	**THAAD PK**	**THAAD FOV**	**THAAD Shot #**	**Patriot PK**	**Patriot FOV**	**Patriot Shot #**
Baseline	0.7	SLS	0.7	120	SLS	0.75	60	SS
Radar Update	0.7	SLS	0.7	120	SLS	0.75	360	SS
SoPhie	0.917	SLS	0.917	120	SLS	0.9825	60	SS
DeepGlo	0.875	SLS	0.868	120	SLS	0.93	60	SS
Shot Update 3	0.7	CSSS	0.7	120	CSSS	0.75	60	CSSS
Shot Update 1 & DeepGlo	0.875	CSSS	0.868	120	CSSS	0.93	60	CSSS
Radar & Shot Update 2 & DeepGlo	0.875	CSSSS	0.868	120	CSSS	0.93	360	CSSS
Radar & Shot Update 3 & SoPhie	0.917	CSLS	0.917	120	CSSS	0.9825	360	CSS
Shot Update 4 & SoPhie	0.917	CSSS	0.917	120	CSLS	0.9825	60	CSSS
Radar & Shot Update 4 & DeepGlo	0.875	CSSS	0.868	120	CSLS	0.93	360	CSSS

Leveraging SmartSet, the team generated a Japan defense scenario using both land-based and sea-based assets. The geographical area of operations included the entirety of Japan with two key defended areas, Okinawa and Tokyo. The available assets include three Aegis systems, two Patriot systems, and three THAAD systems. The Patriot system encompasses the lower-tier defense, the THAAD system encompasses the upper-tier defense, and the Aegis system encompasses the sea-based defense. The defense scenario faces thirteen IRBM threats and four hypersonic threats. The baseline results are displayed in Figure 4 while Figure 5 shows an example of a threat timeline for the first hypersonic threat. Figure 4 displays summary results to include threats launched, destroyed, and leaked which represents threats that reached the defended area. The missile defense assets engaged one of two hypersonic threats and destroyed none. Within Figure 5, the y-axis shows the different hostile and defensive systems while the x-axis shows their activation time in seconds, and the different systems and when the interceptor either destroyed the target, self-destructed, or missed. For example, the PAC-3 interceptor destroyed the hypersonic threat at 472 seconds.

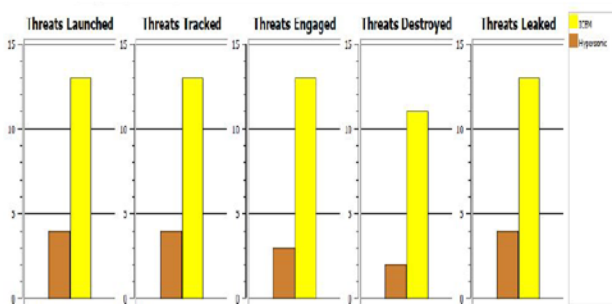

Figure 4. Baseline Simulation Results (Courtesy of Lockheed Martin)

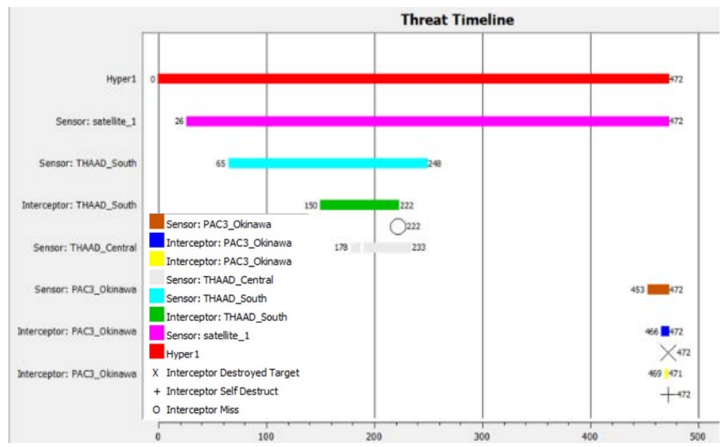

Figure 5. Threat Timeline for Hypersonic #1 (Courtesy of Lockheed Martin)

The next alternatives the team generated represented AI's incorporation as the client has a specific focus on AI for air defense. SoPhie, an AI framework for trajectory prediction, utilizes a generative adversarial network (GAN) designed to predict the path of pedestrian traffic (Sadeghian, 2019). By using a past and current situation, SoPhie develops multiple potential paths until one has at least 50% similar data to the actual situation. In both pedestrian path and missile trajectory, the only information known to the machine is the current position of the entity or missile, the course it has already taken, and possible end states. SoPhie was shown to increase prediction accuracy from a baseline linear regression model by 21%, therefore the team was able to assume the same results could be replicated in missile defense. Based on the similarities between problem sets, the team decided to represent the SoPhie alternative by increasing the PK by 21% for each interceptor system.

The team's other AI alternative algorithm, DeepGlo, utilizes time-series data for path prediction. DeepGlo employs a hybrid model structure coined Temporal Convolutional Network Regularized Matrix Factorization (TCN-MF). The model leverages global and local features to incorporate patterns as separate dimensions within itself when factoring in local features (Sen, 2019). Similarly, the DeepGlo model increased the prediction accuracy of time-series data by 18% also compared to a baseline linear regression model. As radar is a type of time series data, this algorithm could be utilized for hypersonic use cases. Tracking a threat at time x has a given set of coordinates in a multi-dimensional graph which at x + 1 has a separate set of coordinates. To best represent the implementation of a DeepGlo algorithm the team increased PK by 18% for interceptor systems.

After gathering the initial simulation results, the team worked with Lockheed Martin to develop a stochastic model that accurately represents the variability in each alternative. Due to the minimal real-world usage of air defense assets, such data revealed the system's effectiveness as distributions rather than a single point estimate. Each alternative had a distribution for total shots, hits, waste, threats leaked, percent kill, and cost. These distributions were based on 10,000 iterations per alternative, and value functions converted the raw simulation data into value scores.

3. Results

To begin the analysis, a Cumulative Distribution Function (CDF) seen in Figure 6 was overlaid for each of the 26 alternatives. Based on the grouping of the alternatives, the team selected nine alternatives that spanned the decision space. By selecting these nine alternatives and replotting them in a CDF, useful comparisons can be made. The baseline is shown in black, with all other alternatives being an improvement from the current missile defense system that is in place.

The CDF in Figure 6 reveals that when compared to all alternatives, the RS3S alternative is stochastically dominate. Based on each alternative's distribution of value score, other competitive alternatives include SoPhie and S4S. Further analyzing these alternatives, the team generated boxplots for both cost and value, found in Figure 7 and 8 respectively. Figure 7 clearly displays that the RS3S alternative has a higher median value than both S4S and SoPhie. SoPhie and S4S both present significant overlap which shown through both the inter-quartile range as well as maximum and minimum values. Through value analysis, it is evident that RS3S is the most feasible solution; however, it is critical to also analyze the stochastic cost modeling to explore the trade space fully.

The information available about current applications of AI in the Department of Defense (DOD) and the information about the cost of individual interceptors, the team conducted cost analysis. An average cost of $12 million annually for each AI program was determined by evaluating the total funding provided by the DOD to various AI projects (Government Accountability Office, 2022). The team assigned an annual cost of $12 million for the corresponding AI's development time. For SoPhie this is four years and for DeepGlo this is three years. The cost of each individual interceptor was also critical to the development of the stochastic model. Each PAC-3 interceptor shot in a simulation scenario costed $4 million while Aegis and THAAD each costed $12 million. Finally, the team determined the cost of additional radars for alternatives with a "Radar Update," which increased the cost of those alternatives by $30 million. The team combined the above costs and then applied them to each iteration in the Monte Carlo simulation. The cost of each Monte Carlo iteration is distinct due to the variability of missiles used, additional radars, and implementation of AI for each run of the simulation. The uncertainty of cost is significantly related to PK, which dictates in each iteration how many interceptors must be shot to eliminate the threat. This method of evaluating cost created a range of values for the cost shown in Figure 8.

Once the team determined the value of each alternative and their respective costs, the alternatives were plotted to conduct a trade space analysis of the data. This analysis, displayed in Figure 9, is comparing alternatives in terms of cost (x-axis) and total value (y-axis). Referencing Figure 9, the most desirable alternative will be oriented high on the y-axis and low on the x-axis. Figure 7 displays the alternatives with the highest values consistently are RS3S, RS4D, S4S, and SoPhie. Each of these alternatives display that they are the highest-scoring alternatives but when factoring the cost of each alternative as well, Figure 8, the most beneficial alternative is the "Sophie" alternative, with a median value score of 78.95 and median cost of $237,612,800. This is due to the cost of this alternative, which is much lower compared to that of the other alternatives while maintaining a high-value score. The other alternatives incorporate factors on top of the baseline to include a radar update and changes to shot doctrine, yet these factors greatly increase cost while having diminishing returns on value. The team recommends the SoPhie alternative as the best solution for implementation to current air defense assets.

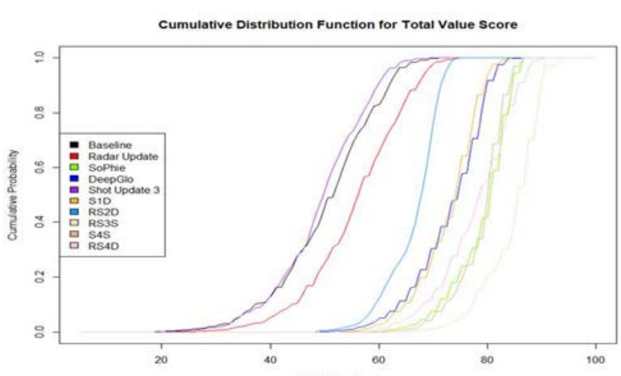

Figure 6. Cumulative Distribution Function for Total Value Score

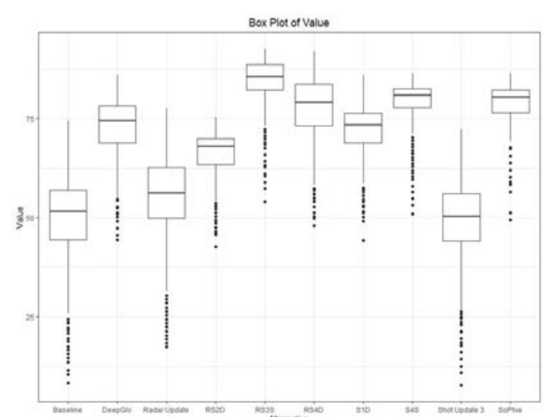

Figure 7. Total Value Score Boxplot

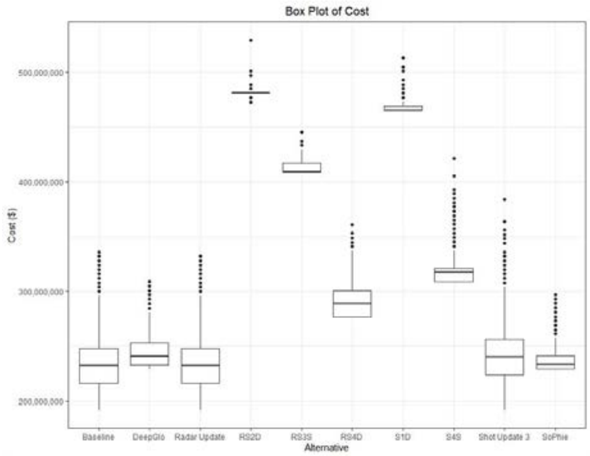

Figure 8. Total Cost Boxplot

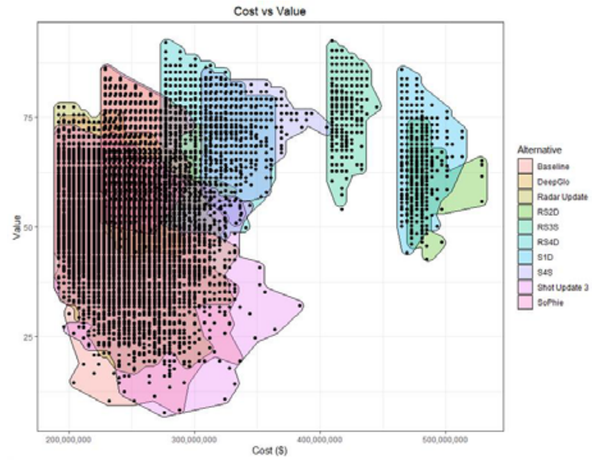

Figure 9. Total Cost vs Value

4. Conclusion

This research sought to determine the viability of applying AI to air defense assets. The team began with the SDP, using this as a framework for the project. Beginning with the problem definition phase of the process, the team conducted stakeholder analysis to better understand the question and how to properly frame the problem. The team then created a value hierarchy with six relevant value measures. The team developed a scoring system for the alternatives that transferred the raw data into a weighted value score using value functions and swing weights. Working with Lockheed Martin, the team was able to simulate each of the 26 alternatives and incorporate them into a Monte Carlo simulation. These iterations enabled the team to create value score distributions for each of the alternatives as well as understand the cost distributions. The team then completed trade space analysis that evaluated the cost and value of each alternative. When evaluating solely value score the team concluded that there was a main grouping of alternatives that present a potential solution. These alternatives are RS3S, S4S, and SoPhie. Analyzing the stochastic cost of each revealed that SoPhie presents the best value at cost. The team confirmed this conclusion through trade space analysis. The recommended alternative, SoPhie, has a median value of 78.95 with a median cost of $237,612,800. This data provides evidence that there is a benefit to including AI in air defense. Future work should include research into how to best implement this technology into air defense assets. Additionally, this research can be refined to better estimate costs and focus on AI implementation into air defense assets to combat hypersonic threats.

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