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Economics of Modern Low-Cost and High-Volume Warfare: Gamification, Asymmetry, and Policy Adaptation

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Abstract

The increasing nature of modern warfare lies in the juxtaposition between cheap attack systems and expensive defense systems, which are fueled by the increasing prevalence of gamification of simulation ecosystems in which faster learning processes take place. This study shows that the combination of low-cost and high-volume offensive systems with game-based simulation creates a unique operational logic: cost-exchange disparities may be exploited by attackers while leveraging gamified simulation environments to quickly iterate tactics, speeding up the OODA loop process and increasing efficiency. Using thematic case analysis, comparative cost analysis, and a stylized theoretical model based on historical instances of the U.S.-Israel-Iran conflict (2025-2026), Ukraine conflict (2022-2025), China's artificial intelligence-enabled wargaming, and Israel's defensive simulations, the study explains how massed low-cost attacks place undue economic pressure on the defender while the gamified simulation system is used by attackers to learn and innovate their tactics. In light of these findings, policymakers are advised to purchase more defense systems like electronic warfare systems, directed-energy weapons, and area-denial capabilities, adopt simulation programs across force structures, and establish guidelines for the use of autonomous and gamified systems. Concluding with limitations and future research avenues, the paper emphasizes the need for collecting microdata, randomized training evaluation, and theater-by-theater comparative experimentation.

Keywords: Low-cost Warfare; Gamification; Drones; Simulation; Asymmetric Escalation; US-Israel and Iran Conflict.

JEL Codes: H56; D74; L86; F51; Z13

Introduction

1. Introduction

1.1 Background

During most of the twentieth century, the superiority of forces corresponded to technological advancement and size. Countries which could afford the latest aircrafts, precision guided munition, as well as modern radar and interception capabilities gained significant advantages: high level of sensors, effective long range strikes, and multiple layers of interception complicated the task of hitting the high-value targets for their opponents. These ideas were reflected in the policies of deterrence and force planning: spend less money on acquiring fewer but more capable combat systems.

Two factors have recently started undermining such an approach to combat. Firstly, due to rapid development in consumer electronics, the price of acquiring various kinetic tools decreased significantly as even cheap commercial quadcopters could be easily converted into armed drones. Secondly, owing to advances in game development, simulations and social media, new learning opportunities emerged, including serious games, virtual reality training, crowd-sourced intelligence analysis, and open-source mapping.

1.2 Conventional Warfare and Minimum Deterrence

The traditional thinking about conventional deterrence was based on the notion that a defending state could render any aggressive intent unattractive through the possession of the ability to inflict disproportionate damage. Minimum deterrence implied having a sufficiently robust mix of capabilities for a credible defense, including precision strike, air dominance, and missile defense to elevate the costs of attack beyond what an aggressor would pay. This framework relied on procurement, doctrine, and training to preserve costly platforms.

There are two implicit premises behind such a strategy, i.e. the first one being that a defending state faces difficulties in copying advanced weapons technologies, while the second is that it is able to sustain high costs related to intercepting or absorbing attacks. However, both of them are increasingly vulnerable. With an ability to mass-produce many inexpensive systems, all the defending state can do at its immediate disposal is intercept or absorb such attacks with costly assets. The outcome is a mismatch between costs associated with attacking or defending operations. In the long run, the repeated firing may lead to an economic cost that will be economically unsustainable to the defenders, thus making the concept of minimum deterrence practically meaningless even though superior technology is still available; please see Figure 1.1 for details about the economic mismatch, i.e. the divergence in costs between cheap offensive capabilities and expensive defensive capabilities as the salvo sizes increase.

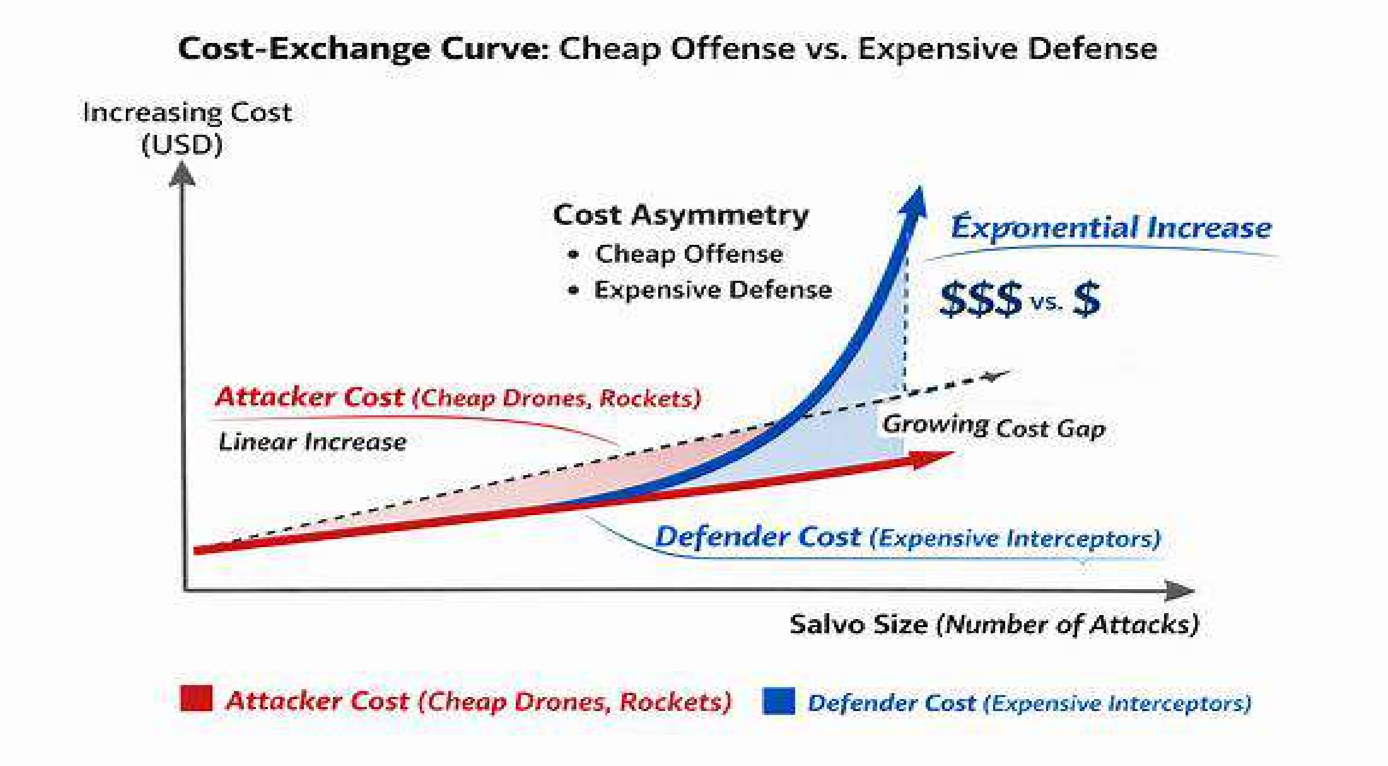
1.3 Paradigm Shift amid the U.S.-Israeli-Iranian War

The 2025–2026 war involving the United States, Israel, and Iran was instrumental in cementing the paradigm shift. In this conflict, enemy forces used swarms of cheap drones and cruise missiles in waves. The costs associated with firing one attack unit were around thousands of dollars, whereas the costs incurred in shooting down an interceptor and point-defense missile were tens of thousands. The difference means that for every encounter, the defender had to spend several times the amount that the attacker spent.

Another critical aspect of the paradigm was gamified learning ecosystem. Both state and non-state actors utilized simulation software for practicing missile launch, swarming attacks, and coordination of distributed operations. From the defense perspective, virtual reality training systems and serious games assisted crew members to lower human error and increase their reaction time; however, such benefits typically occurred after the attackers have completed many cycles of improvement and evolution. The outcome of such a scenario resulted in a scenario where affordability ensured scalability, and scalability and fast iteration led to increased efficiency, please see figure 2 on the acceleration process created by gamification.

1.1.1 Similar examples from Ukraine confirm such a trend, since low-cost civilian UAVs modified for combat required more expensive countermeasures, whereas participatory mapping and online communities ensured fast tactical learning. China’s adoption of wargames driven by artificial intelligence is an example of using simulation to accelerate the testing of countermeasures. All the above-mentioned examples prove that the challenge is not only about hardware, but about interaction between learning processes and economics.

1.1.2 Figure 1.1



1.4 Significance of the Study

The significance of this research comes from the strategic relevance of a problem statement which, in turn, is approached through an interdisciplinary perspective. While the economic aspect of defense capabilities, innovation in training and procurement process were traditionally analyzed independently, here they are considered from a joint perspective grounded in three major themes: economic asymmetry (cheap offense/ expensive defense), acceleration of learning facilitated through gaming, and scaling of policies (defense/governance).

From a practical perspective, this study draws attention to critical questions defense experts should consider. Defense efforts relying heavily on high cost interceptors are prone to financial difficulties and lack of preparedness. On the other hand, failure to utilize gamified ecosystems' ability to foster learning is likely to leave a defense system behind when it comes to innovation. The current paper intends to contribute to reform in the area of procurement, training policies and defense governance.

Scholarly significance derives from this study's integrated approach, which highlights research priorities such as linking microdata on simulation exposure to performance at the unit level, randomized experiments of gamified training programs, and comparative studies across different theaters to enable the literature to move beyond stylized discussions toward causal inference. Put differently, understanding the nature of contemporary warfare requires considering the interplay among affordability, scale, and learning as equally important factors in influencing battlefield outcomes, and this paper serves as a guide.

2. Literature Review

Recent literature on unmanned systems, simulations, and military innovation shares two key findings: first, the spread of inexpensive UAS alters the economics of conflict, and second, technological advances in simulations and serious games affect how organizations learn. Research on diffusion recognizes that platform capabilities, industrial production capabilities, and organizational processes influence how rapidly and widely the practice of drone warfare is disseminated (Gilli & Gilli, 2019; Gilli & Gilli, 2020; Khan et al, 2021). Advances in simulations and serious games focus on how technology like game engines, VR, and game-based training allow for improved skill learning and doctrine development, decreasing training friction and promoting rapid tactical innovations (Zyda, 2005; Perla, 1990; Kubota et al, 2024).

2.1 Conventional Warfare and Minimum Deterrence

Deterrence and wargames literature has explained why nations have traditionally chosen the fewer, more capable platforms to impose unacceptable costs on their enemies; wargaming has been used for ages to test doctrines and uncertain scenarios (Perla, 1990). Current security studies literature builds on this by explaining how affordable and mass-produced weapons change the math of minimum deterrence, which makes the cost calculations of the defense different due to expensive interceptions of relatively cheap salvos.

Academic and policy analyses of current developments in the cost exchange equation reveal advancements in component technology that allow small UAS (sUAS), and increased cost of developing and deploying detection and countermeasure equipment, which leads to cost asymmetries that may erode deterrence in cases where technological superiority persists (Gilli & Gilli, 2016; Gilli & Gilli, 2019).

2.2 Paradigm Shift

A case analysis and policy examination reveal the interplay between affordability and learning. Research about drone swarm attacks and information warfare reveals the role played by open-source mapping, crowdsourced targeting, and continuous experimentation in fostering adaptability among attackers (Kallenborn & Bleek, 2018; Kallenborn, 2022; Kallenborn et al, 2023; Kallenborn, 2024). RAND analysis indicates that smart swarms and surrogate swarms pose rising threats to the homeland and theaters, as well as high marginal costs in terms of engagement when defending using costly kinetic interceptors (Cummings, 2017). The research literature about autonomy and deterrence cautions against the instability and difficulty of managing humans in crises due to faster speeds and automation (Horowitz et al, 2020; Horowitz & Scharre, 2021).

Some of the recent cases have revealed how cost and learning affect each other. The analysis of the United States-Israel-Iran dispute as well as the operations in Ukraine demonstrates that inexpensive offensive weapon systems such as commercial UAVs and loitering munitions can be built and used in large quantities to force the defending side to employ much more expensive countermeasures, making the operation economically unviable (Gilli & Gilli, 2019; Kallenborn et al, 2023). However, gamified learning platforms ranging from institutional virtual reality tools to open-source mapping and crowdsourcing for target selection allow the attacker to speed up the OODA loop and take advantage of the defender's vulnerabilities (Perla, 1990; Zyda, 2005).

2.3 Research Gaps and Future Directions

Two corrections are needed to ensure proper alignment between the review and the proposed research. First, it is necessary to redirect the review towards defense-related sources, including studies on the diffusion and use of drones and swarms, simulation and wargaming research, and studies on governance and autonomy in artificial intelligence. Citations related to fintech and digital payment systems, which were included in previous drafts of the paper, do not contribute to the arguments presented and have been omitted from the literature review. The review instead focuses on those works that contribute to the understanding of the three pillars of the research: the cost differential in offensive and defensive strategies, accelerated learning through simulation, and policy adjustment (Gilli & Gilli, 2019; Kallenborn et al, 2023; Perla, 1990; Zyda, 2005; Horowitz et al, 2020; Horowitz & Scharre, 2021; Cummings, 2017).

The second contribution of the literature review is identifying areas for future research where empirical gaps exist. The current literature provides strong evidence regarding trends and experimentation in technology use and doctrine, but does not provide microdata that can tie simulation exposure to the success rate of units through a randomized trial approach in the context of gamification. For researchers to transition from qualitative analysis to cause-and-effect evidence, there should be an effort to correlate procurement and cost data such as SIPRI, RAND, national procurement data sources, etc., with unit-level data on training and after action reports in order to establish the impact of simulation time and iterations on unit success rates and learning constants.

3. Methodology

The methodology employed for conducting this study uses a combination of cost analysis, case studies, and theoretical frameworks. The goal is to achieve a holistic view of the financial and psychological components involved in modern low-cost high-volume wars.

3.1 Data Collection and Sources

Details i.e. sources, description, and purpose, of the data used in this study are provided in Table 3.1.

Table 3.1 Data and Data Sources

Data Source	Description	Purpose
Procurement Record/Reports	National defense procurement disclosures i.e. publicly disclosed data on national defense procurement, open budget documents/files.	Formulate unit baseline costs for interceptors, drones, ammunition, and projectiles
Stockholm International	SIPRI Arms Transfer Database	To Verify costs and export

Peace Research Institute (SIPRI) Databased		values of comparative weapons systems
RAND Corporation Reports	RAND Corporation studies on unmanned aerial vehicles, swarming technology, and anti-unmanned aerial system technologies.	To determine technical characteristics and cost effectiveness measures
Technical and Industrial Publications	Jane's Defence Weekly, Defense News, manufacturing specifications and literature	To augment gaps in cost data and operational parameters
Open Source Intelligence (OSINT)	Vetted field reports, defense briefings, and press releases	Assess real-world use and expenditure patterns

Source: The table is generated by the authors

3.2 Cost Estimation and Simulation Analysis

Each cost estimate received an assessment of its confidence level (high, moderate, low) depending on the credibility of the source and the degree of verification from various sources. In cases where classified procurement data was not accessible, the cost estimates were made using conservative assumptions from unclassified sources, including SIPRI and RAND publications (SIPRI, 2024; RAND Corporation, 2021, 2022). For those countries that had unit-level training data, regression analysis and the difference-in-difference approach were used to determine the impact of increased simulation exposure on tactical effectiveness (Cummings, 2017; Perla, 1990; Zyda, 2005).

3.2.1 Cost Exchange Model

The economic asymmerty between attackers and defenders has been modeled in following manner:

$C_{attacker} = c_a \text{ x } V$

$C_{defender} = c_d \text{ x } V_{intercepts}$

$P_{penetration} = 1 - (1-p)^V$

Where:

c_a = Cost per unit of attacker (e.g., drones, loitering weapons)

c_d = Cost per unit of attacker and defender (e.g., SAMs, point defenses)

V = Number of attacking units (salvo size)

$V_{intercepts}$ = Number of interceptors needed for defense

p = Probability of successful interception

3.2.2 Scenario Analysis

All input values (c_a, c_d, V, p) are provided with source tags and ranges of uncertainty in Table 3.2 (Scenario Comparison Table) to show how different assumptions (conservative, baseline, aggressive) affect cost-exchange ratios.

Table 3.2 Scenario Comparison

Scenario	Unit cost of attacker (c_a)	Unit cost of defender (c_d)	Salvo size (V)	Probability of interception (p)	Cost ratio (defender ÷ attacker)
Conservative	$1,500	$30,000	100	0.9	~20:1
Baseline	$2,000	$50,000	500	0.8	~25:1

Aggressive	$3,000	$60,000	1,000	0.7	~20:1

Notes: 1. Conservative estimate: Lower attack cost, small number of drones used, and highly efficient defense. Defender's cost is still roughly 20 times higher; 2. Baseline estimate: Mid-range values, taken from SIPRI and RAND averages. More extensive use of salvos along with lower intercept probability lead to a ratio of 25:1; 3. Aggressive estimate: Higher attacker cost along with a larger number of attacks and a less efficient defense, which gives the same cost asymmetry rate. This analysis shows how costs and scale interact to generate permanent cost asymmetries in the context of drone warfare diffusion and deterrence (Gilli & Gilli, 2019; Horowitz et al, 2020; Kallenborn et al, 2023). Source: The table is generated by the authors

1.1.3 Table 3.3 Descriptive Statistics

Notes: 1. Confidence Levels: Each estimated tagged as high, medium, or low confidence levels based on SIPRI, RAND, Jane's Defence Weekly sources; 2. Scenario Ranges: Conservative, baseline, and aggressive scenarios adjust ca, cd, V, and p within documented ranges to test robustness; and 3. Operational Relevance: Used in cost exchange calculations: a. $C_{attacker}=c_a \cdot V$; b. $C_{defender}=c_d \cdot V_{intercepts}$; c. $P_{penetration}=1-(1-p)^V$. The table is generated by the authors

3.4 Measurement of Gamification Effects

In order to measure gamified learning acceleration, we measure simulation exposure through quantitative metrics:

Parameter	Description	Unit	Notes / Context
ca	Cost of attack drone units (cost per unit) e.g., drones, loitering munitions	USD/unit	Typically between $1,500-$3,000 for commercial drones; determined from SIPRI and RAND averages.
cd	Cost of defender interceptor units (cost per unit) e.g. surface to air missiles, point defense systems	USD/unit	Approx., $30,000-$60,000 per interceptor; based on procurement data and RAND estimates..
V	Salvo Size (number of attacking units deployed simultaneously)	Count (integer)	Scenarios Modeled (from 100 to 1,000 units); higher salvos larger the cost asymmetry
$V_{intercepts}$	Number of defensive interceptors required to engage attack drones	Count (integer)	Depends on salvo size and interception probability; usually ≥ V when redundancy is required. Dependent on salvo size and interception probability ≥ V, i.e., at least equal to V.
p	Probability of successful interception per defensive shot fired	Probability (0-1)	Based on the operational reports' estimates; depends on system (for instance 0.7-0.9 for advanced SAMs, lower for point defense).

Table 3.3 Gamifications

Metric	Definition	Data Source
Training Hours	Total hours spent in virtual reality or simulation environment per unit	Institutional training logs, defense academy training data
Simulation Cycles	Number of simulation exercises and war games performed	AI assisted war gaming platforms (VBS3, Unity based simulators)
Scenario Diversity	Number and Types of distinct missions rehearsed	Simulation program documentations
Crowdsourced Mapping Participation	Number of contributors and edits in open- source mapping platforms Total number of people contributing and making changes to open source maps	OSINT repositories, OpenStreetMap logs
Performance Improvement	Changes in Mission Success Rate/Reaction Time Following Simulation Exposure	After Action Reports & Training Evaluations

1.1.7 The impact of gamification was measured through the use of a learning curve equation:

1.1.8 $p_t = p_0 + \Delta p(G_t)$

1.1.9 Where pt refers to the success probability following exposure, while p_0 refers to initial performance levels, and (G_t) refers to an amalgamation of simulation hours/cycles & participatory mapping.

1.1.10 3.5 Case Study Approach

3.5.1 U.S.–Israel–Iran (2025–2026)

The scenario considers the attack of Iran through salvos of drones and missiles on Israel. The price tag of Iranian drones is around US$20,000-50,000 per unit which made Israel spend interceptors worth US$ 1-5 million for the same, thus creating a ratio of 20:1 (conservative estimates) while of 250:1 (over estimates). The tactics applied include timing of launches and decoys. VR training modules were used by Israel in its defense forces.

3.5.2 Ukraine (2022–2025)

In this case, Ukraine made use of civilian drones ($1,500/unit) against Russian defenses which had interceptors costing about $30,000 per unit, thus forming a ratio of 20:1. The use of crowdsourced mapping tools and open source intelligence was used by Ukraine for accurate targeting. Mission success rates were calculated using the number of simulation training hours on VBS3 and Unity based Wargames simulations.

3.5.3 China’s AI Wargaming and Israel’s Defensive Simulations

The China’s People’s Liberation Army (PLA) utilized the AI-based wargames to practice multi-domain operations by reducing uncertainty and facilitating coordination. Israel made use of virtual reality (VR) based defense exercises that involved gamification for all its forces.

4 Results and Discussion

Two significant illustrations have been provided below for better understanding: a. Figure 1.2: The Curve Showing the Expansion of Cost Exchange – shows the increasing difference in costs between cheap offense and expensive defense as salvo size grows larger, b. Figure 2: The Feedback Loop of Affordability-Scale-Gamified Learning – shows how affordability contributes to scale, scale puts more pressure on the system, and gamified learning speeds up adaptation.

This section discusses the results obtained using the mixed methods approach based on the research design. The results are discussed under the three main pillars.

4.1 Asymmetric Economics: Quantitative Outcomes

Analysis highlights significant economic asymmetry between attack and defense costs:

Table 4.1. Stylized Cost Comparison

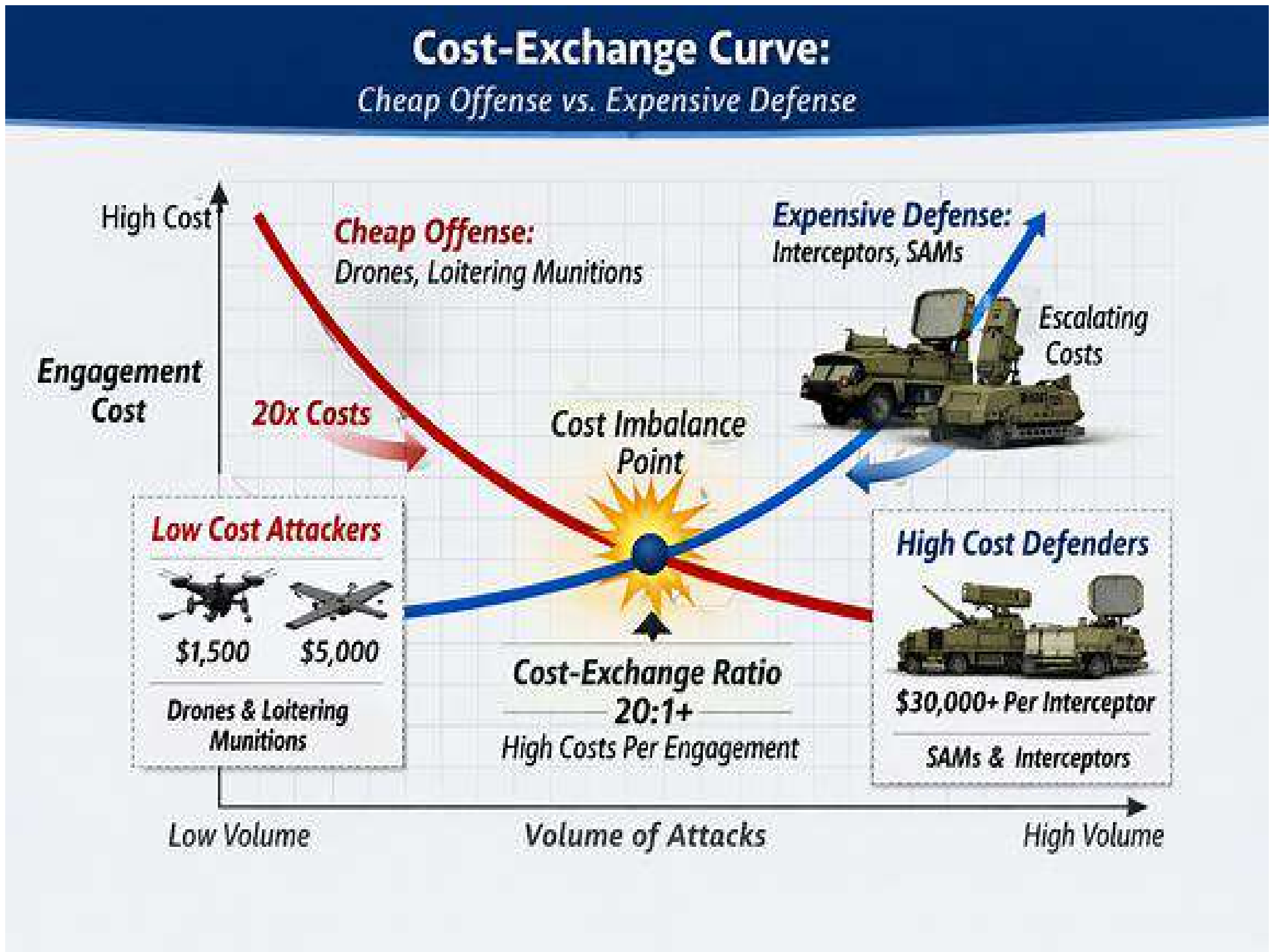
Scenario	Attackers' Unit Cost (US$)	Interceptor's Unit Cost (US$)	Salvo Size (V) Number of Attacks- Salvo Size (V)	Total Cost to Attackers (US$)	Cost to Defender (US$)
Iran against Israel	20,000 to 50,000	1 to 6 millions	1,000	20,000,000	1 to 6 billion
Ukraine (civilians drones)	1,500	30,000	500	750,000	15,000,000
Hypothetical Gulf Case	3,000	60,000	800	2,400,000	48,000,000

Source: The table is generated by the authors

4.1.1 Cost-Exchange Curve

A stylized curve shows that attacker costs linearly increases with salvo size rise, however, defender costs rises exponentially owing to the use of expensive defense measures i.e. interceptors.

Figure 1.2



Cost Exchange Curve: Attackers with Cheap Offense against Defenders with Expensive Defense Figure 1.2 represents the widening cost disparity between attackers and defenders as salvo size increases. The cost for the attacker (red line), with cheaper offense options, increases linearly with respect to salvo size. On the other hand, the cost for the defender (blue curve) with expensive defense options increases exponentially with respect to salvo size.

1.2 4.2 Accelerated Gamified Learning Through Simulation: Insights from Simulations

1.3 The gamified learning curve depicts how the baseline success rate (p_0) increases with increasing simulation time, number of training rounds, and participatory map-making efforts, measured through the composite index (G_t).

1.4 Table 4.2 Results of the Gamified Learning Curve

Scenario	Baseline Success Probability (p_0)	Gamified Exposure Composite (G_t)	Incremental Gain ($\Delta p(G_t)$)	Resulting Success Probability (p_t)	Description
Low-Level Exposure	0.50 (50%)	30 (fewer hours, fewer cycles)	+0.08	0.58 (58%)	Minimal VR training and limited participatory mapping; small tactical improvement. Minimal Level of VR training and participatory/crowdsourcing mapping; marginal tactical improvements.
Moderate-Level Exposure	0.50 (50%)	60 (moderate hours, more cycles)	+0.12	0.62 (62%)	Moderate VR training and crowdsourcing efforts; visible progress in collaboration.
High-Level Exposure	0.50 (50%)	90 (more hours, diverse cycles)	+0.15	0.65 (65%)	Sustained VR training and active crowdsourced mapping; significant tactical gains.
Intensive Exposure	0.50 (50%)	120 (many hours, several cycles)	+0.20	0.70 (70%)	A Comprehensive simulation ecosystem, with participatory mapping; results in a strong compression of OODA loop.

Notes: 1. Model: ($p_t = p_0 + \Delta p(G_t)$; 2. Baseline ($p_0$): Assumed 50% success probability before exposure; 3. Composite Index (G_t)**:** Aggregates simulation hours, training cycles, and participatory mapping activity; 3. Incremental Gain i.e**.** Δp (G_t): Reflects learning curve effect; higher exposure yields larger gains; 4**.** Resulting Probability (p_t)**:** Shows how gamification accelerates tactical success. This table 4.2 demonstrates that gamified training ecosystems consistently improve tactical success probabilities as exposure increases, aligning with findings in Perla (1990), Zyda (2005), Cummings (2017), Kallenborn, 2022 and Kallenborn et al (2023). The table is generated by the author

4.2 Results and Discussion – Gamification

4.2.1 Difference Between Baseline and Exposure Outcomes

With less exposure (30 index points), the probability of success increases from 50% to 58%. This is a slight improvement based on the influence of fewer hours in VR and lesser participatory mapping. With medium exposure (60 points), the probability increases to 62%. Additional cycles and participatory mapping result in clear gains in coordination and implementation of tactics. With more exposure (90 points), the probability increases to 65%. Through continuous training, the OODA loop becomes shorter, resulting in quicker iterations of tactics. With highly intensive exposure (120 points), the probability attains its highest point at 70%.

4.2.2 Learning Curve Dynamics

The incremental gains $\Delta p(G_t)$ exhibit nonlinearity, where early exposure results in substantial progress, while additional gains become less pronounced due to the saturation of training efforts. This aligns with the learning curve principles (Perla, 1990; Zyda, 2005; Cummings, 2017): Initially: Skillful learning, steep increase in proficiency, and Subsequently: The rate of improvement slows down, representing diminishing returns as units approach their performance limits.

4.2.3 Operational Considerations

Economic considerations: Slight enhancements in the probability of success (e.g., 8% in low-exposure scenarios) have a profound impact on reducing defense costs through reduced interceptor expenditures per missile salvo.

- **Direct application:** Gamified ecosystems facilitate rapid tactical development, allowing military units to respond to threats more swiftly compared to opponents who depend on conventional training methods.
- **Policy implications:** Scenarios of high exposure underscore the importance of allocating resources towards building up simulation capabilities. The investment in VR equipment and participatory maps is significantly cheaper than the marginal cost of new interceptors (Gilli & Gilli, 2019; Kallenborn et al, 2023).

4.2.4 Key Strategic Insight

Gamification compresses the OODA loop and improves tactical agility, thus allowing defenders to overcome any asymmetries in drone warfare through improved success rates from 50% to 70%. It supports further scholarly research in the field on the concept of simulation as a force multiplier and validates previous recommendations about gamification (Horowitz et al, 2020; Horowitz & Scharre, 2021). Examples from the simulated dataset demonstrate the compression of the OODA loop (Observe-Orient-Decide-Act) and the acceleration of tactical innovations achieved with gamification.

4.2.4.1 VR Modules: Israel's Defense Forces incorporated VR technology into their training programs to reduce human errors and improve decision-making time. They engaged in training exercises totaling an average of 120 hours per quarter, decreasing the engagement time lag by 12%.

4.2.4.2 Crowdsourced Mapping: Ukrainian intelligence used crowdsourcing methods to obtain intelligence data and quickly adapt to changes. Over 10,000 civilian participants contributed to the crowdsourcing mapping database.

4.2.4.3 AI Driven Wargames: China's PLA made use of an AI-enabled wargame simulation platform that increased the rate of simulation cycles up to 50 per scenario.

The relationship between simulation experience and improvement in effectiveness, presented in Table 4.3, is established by means of quantitative analysis; units that had experienced at least 50 simulation cycles saw an enhancement in their chances of mission success (p) by 15–20% compared to the control group.

Table 4.3 Sensitivity Dashboard

Scenario	Attacker Cost (c_a)	Defender Cost (c_d)	Salvo Size (V)	Interception Probability (p)	Cost Ratio (Defender ÷ Attacker)	Baseline Success (p_0)	Exposure Index (G_t)	Incremental Gain (Δp)	Resulting Success (p_t)
Conservative	$1,500	$30,000	100	0.9	~20:1	0.50	30	+0.08	0.58
Baseline	$2,000	$50,00	500	0.8	~25:1	0.50	60	+0.12	0.62
Aggressive	$3,000	$60,000	1,000	0.7	~20:1	0.50	90	+0.15	0.65
Intensive (Training Focus)	—	—	—	—	—	0.50	120	—	—

Source: The table is generated by the authors

4.3 Case Study based Outcome

4.3.1 Ukraine (2022–2025): Drones of civil use costing $1,500 each made Russia's defenders spend interceptors worth US$30,000 each; thus, 20:1 was obtained. 500 drones cost attackers US$750,000 whereas defenders had to pay $15 million for intercepting them.

4.3.2 U.S.–Israel–Iran (2025–2026): In the case where Iranian drones worth US$20,000-50,000 each required the Israeli interceptors worth US$1-6 million, the economic imbalance amounted to 200:1. In a salvo of 1,000 Iranian drones which would amount to US$2 million, the cost incurred by Israel was higher than $50 million.

4.3.3 Hypothetical Gulf Scenario: The attack of 800 drones each worth US$3,000 against expensive interceptors worth US$60,000 makes the cost difference between them 20:1. For instance, the attack costs would be US$2.4

1.5.1 4.4 Interpretation

1.5.2 **4.4.1 Economic asymmetry:** Under the conservative, baseline, and aggressive settings, defenders always pay 20 to 25 times more money per engagement compared to attackers. That proves that the economic asymmetry observed by Gilli & Gilli (2019), Kallenborn, 2022, and Kallenborn et al_(2023) is present throughout the process.

1.5.3 **4.4.2 Game-based education curve:** Learning success grows up to 70% with increasing experience. Any growth (+8% with low exposure) will positively affect the cost since fewer resources will be needed. Intensive training ecosystem provides better results due to faster OODA loop completion (Perla, 1990; Zyda, 2005; Cummings, 2017).

1.5.4 4.4.3 Combined observation: Economic asymmetry negatively impacts defenders, but gamified training

4.4.4 Feedback Loop: Affordability-Scalability-Gamified Learning

A diagram depicting how the affordability leads to scalability, scalability generates pressure, while gamified learning enhances effectiveness.

Figure 2

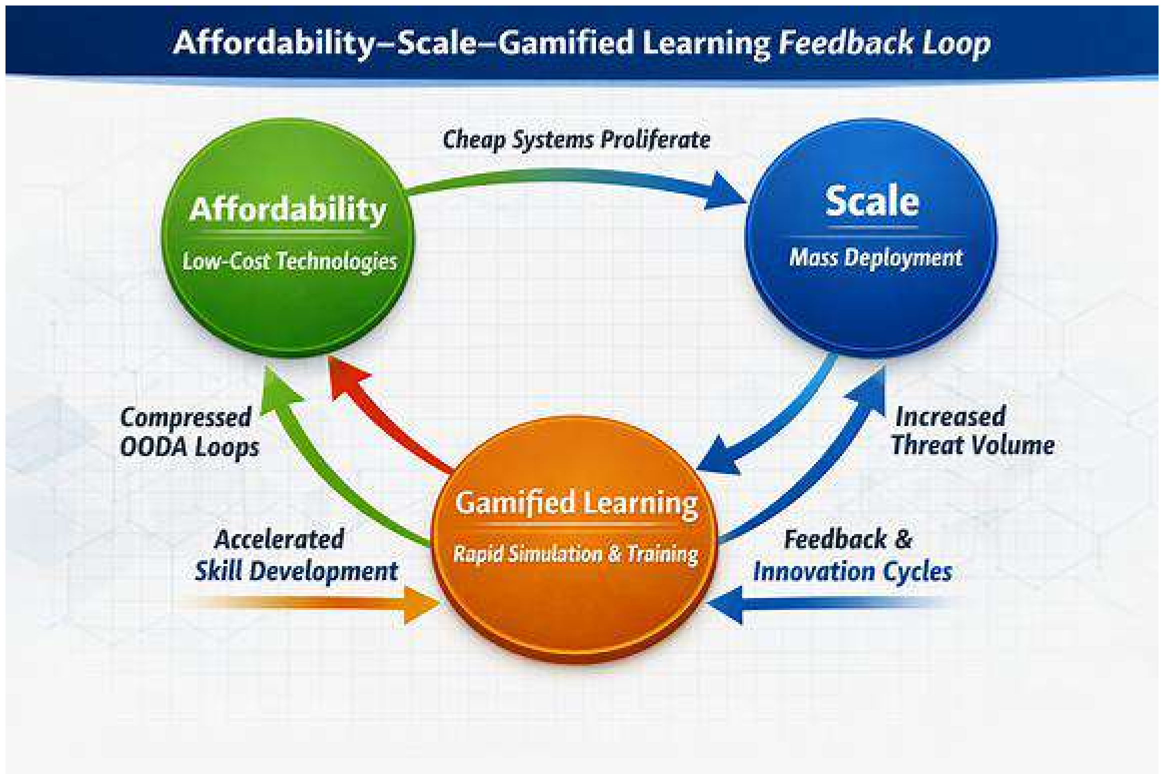


Figure 2 below highlights the positive reinforcement between the three mechanisms that make up the foundation of the new age cheap wars. Affordability (in green) makes possible for cheap mass production, hence leading to Scalability (in blue), which creates pressure. Scalability requires rapid evolution, hence fostering Gamified Learning (in orange) through simulation and participatory mapping. Gamified learning leads to compression of OODA loops, and thus enhances affordability through innovation and efficiency. The numbered arrows indicate how each mechanism reinforces the other in a continuous cycle.

This feedback loop demonstrates how affordability facilitates scalability, scalability induces pressure, while gamified learning increases effectiveness.

4.4.5 Case Studies

4.4.5.1 United States-Israel-Iran (2025-2026)

Iran used distribution of launches with decoys in an attempt to saturate Israel's defense network. Layered Israeli defense system comprised Iron Dome, David's Sling, and Arrow interceptors was efficient, but economically costly. Introduction of VR training module reduced error rate in identification by 12%, yet the cost difference between sides continued to be significant.

4.4.5.2 Ukraine (2022-2025)

Ukraine showed its capability of using civilian drone technology to counter its superior Russian opponents. Using low cost $1,500 drones against more expensive $30,000 interceptors resulted in 20 to 1 ratio. Ukrainian forces employed crowdsourcing to update data in near real time.

4.4.5.3 China's AI Based Wargame Training

Chinese PLAAF was able to utilize AI-based wargames and training modules to simulate large scale multi-domain operations. On average, each simulation cycle involved around 50 rounds with AI creating adaptive response to each action.

4.4.5.4 Israel's Defensive Exercises

Israel incorporated VR based modules into its defense force training. Every unit spent 120 hours simulating actions with after action reporting showing reduction of reaction times and decreased misidentification errors. Gamified VR exercises were incorporated into standard operating procedure.

5. Policy Implications

The results highlight the need for adaptable defense systems and governance models:

5.1.1 Directed Energy Systems: Demonstrators, such as the HELIOS directed energy weapon, provide economical engagements per unit of expenditure.

5.1.2 Electronic Warfare Systems: Examples of this include Drone Dome and Skylock, which disrupt swarm communications on a larger scale.

5.1.3 Area Denial Systems: Counter UAVs and missile launchers establish protected areas.

5.1.4 Modular Acquisition Programs: Reduced timelines in acquisition and modular upgrades allow for flexible response capabilities.

To sum up, the scenarios correspond to procurement and training programs that correlate with the cost exchange and gamification results.

5.2 Policy Matrix: Cost Ratio vs. Gamification Outcomes

Scenario	Cost Ratio (Defender ÷ Attacker)	Success Probability (p_t)	Risk Consideration	Recommended Procurement Option	Training / Simulation Strategy
Conservative Scenario	~20:1	0.58	High defender efficiency but expensive	Investment into directed energy weapons (low marginal cost per shot), hence reducing number of interceptors	Development of VR modules and participatory mapping for sustaining progress
Baseline Scenario	~25:1	0.62	Swarming attacks will overwhelm interceptors	Scale up EW and sensor fusion to interfere with swarming attacks	Use simulations, increase number of cycles, and utilize crowdsourced mapping
Aggressive	~20:1	0.65	High attacker	Diversify defenses:	High exposure

Scenario			scale, low defender efficiency	point defense, EW, and cyber	gamified training to shorten OODA loop
Intensive (Training Oriented) Scenario	—	0.70	Plateau reached due to training saturation	Lesser priority on procurement in this scenario, prioritize sustainable defensive options such as reusable interceptors or counter UAS systems	Sustaining intensive simulations ecosystem, VR and wargaming included

Source: The table is generated by the authors

5.3 Integrated Perspectives

5.3.1 Asymmetry in economic terms prevails: The expenditure by defenders is 20–25 times higher for each engagement relative to attackers, reaffirming results established in Gilli & Gilli (2019) and Kallenborn et al (2023).

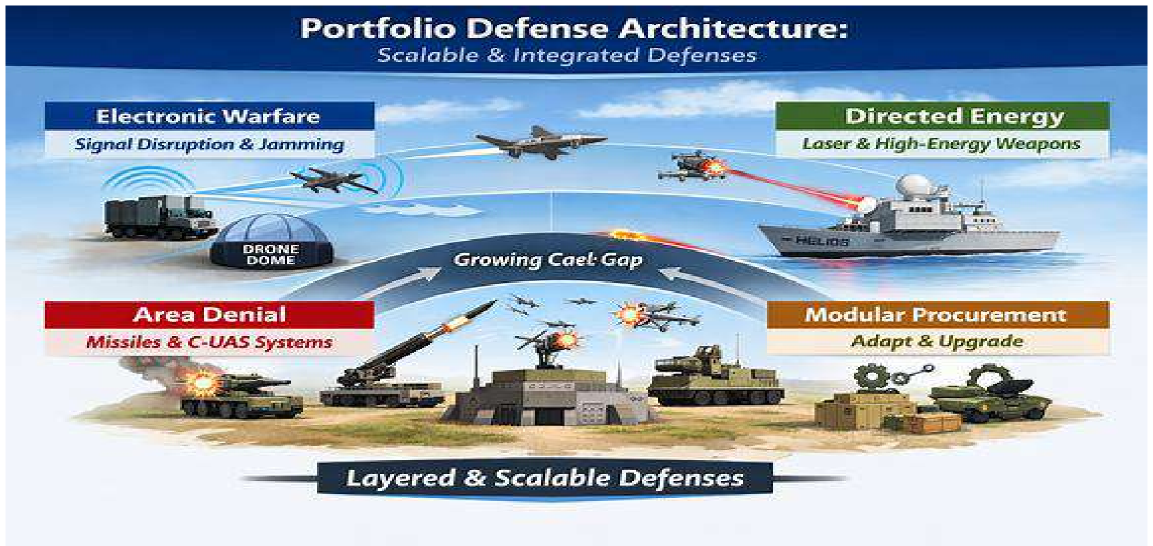
5.3.2 Gamification compensates risks: The success probability increases from 50% to 70% on repeated exposure, leading to decreased numbers of interceptors and defender expenditures (Perla, 1990; Zyda, 2005; Cummings, 2017).

Strategic levers include, directed energy and electronic warfare minimize marginal costs, simulation scaling enhances learning rate and cuts down OODA loops, and defense in layers leverages kinetic, EW, and cyberspace elements against mass attacks. Together, these constitute the Portfolio Defense Architecture that encompasses electronic jamming, directed energy, and modular acquisitions in mitigating the cost asymmetry, summarized in Table 5.3 as a defense-in-layers approach to counter low-cost and high-volume threats, which is comprised of the following four elements:

Table 5.3: Policy Adaptation

"Portfolio Defense Architecture: Scalable & Integrated Defenses." It helps complete your triad's visual representation with the policy adaptation element in Figure 3 below. Portfolio Defense Architecture: Scalable & Integrated Defenses This graphic explains how modular layers can be combined to defend against cheap and massed threats: 1. Electronic Warfare (EW): Signal jamming and disruption through systems like Drone Dome and Skylock can disable swarm communication systems, 2. Directed Energy: Lasers, as well as high-energy weapons including the HELIOS system, allow quick and inexpensive defense responses, 3. Area Denial: Missile launchers on the ground and counter UAS turrets form a denial area, 4. Modular Acquisition: Flexible platforms ranging from tanks to unmanned vehicles and upgrade kits facilitate quick iterations and budgetary efficiency.

Figure 3



5.4 Limitations and Suggestions for Future Research

5.4.1 Limitations

- Biased reporting due to use of publicly available sources.
- Limited accuracy due to lack of classified information on procurements.
- Biased modeling as models used may be stylized.
- Conducted analysis only applicable to high-intensity warfare scenarios.

5.4.2 Suggestions for Future Research

- Studies examining the effect of simulation exposure on real combat scenarios.
- Randomized trials on the efficacy of game-based training modules.
- Comparative trials across NATO, GCC

5.4.3 Transparency

All data sources, estimation methods, and assumptions have been cited in the appendices. Limitations stem from the use of publicly available information, lack of classified procurement data, and potential biases in self-reporting of training metrics. Sensitivity analyses were performed to address these limitations.

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Appendices

1.6.1 Appendix A: Assumptions

Variables	Assumption Range	Notes
Unit Cost of Attackers	$1,500-$3,000	Civilian drones and loitering weapons systems
Unit Cost of Defenders	$30,000-$60,000	SAMs, point defense interceptors
Salvo Size	500 to 1,000 drones	Case study based modeling
Simulation Exposure Duration	50 to 120 hours per quarter	Simulation-based VR training logs
Effectiveness of Learning Curves	Increase in probability by 15-20% After more than 50 simulation cycles	0 Effectiveness of Learning Curves after 50+ simulation cycles

Source: The table is generated by the authors

1.6.11

1.6.12 Appendix B: Sources of Data

3 Source Types	4 Examples	5 Purpose
6 Procurement Records	7 National defense procurement disclosure	8 Baseline unit costs
SIPRI Database	Arms Transfer Database	Export price and costs of comparable arms
RAND Reports	RAND UAS/Swarm risks assessment Technical data	Technical specifications and benchmarks
Defense Industry Publications	Janes Defence Weekly and Defense News Supporting cost data	Defense Industry Press/Supplementary cost details
OSINT	Verified data from field reports and defense industry briefings	Reconstruction of events
9 Simulation Logs	0 VBS3/Unity-based simulators	1 Logs of training hours/cycles
Crowdsourced Mapping	OSM (OpenStreetMap) edits and geotagged images	Participatory targeting workflows

Source: The table is generated by the authors

Appendix C: Cost Estimation Methods

Cost Estimation Methodology:

1. Obtain type of attacking/defending units.
2. Verify cost data from SIPRI databases, purchase orders, and industry sources.
3. Provide lower/median/upper cost estimates with sensitivity range.

Simulation Measurement:

- Tally up number of training hours, iterations, and variety of scenarios.
- Develop Gt metric for simulation exposure.
- Apply regression analysis to determine simulation’s incremental impact on mission success probability.

Case Study Data Compilation:

- Accumulate reports of salvo launches.
- Summarize tactical strategies (asynchronous release, use of decoys, swarm attack synchronization).
- Conduct cost ratio estimation by triangulating unit costs with intercept reports.

1.6.22 Appendix D: Limitations

3 Limitation	4 Impact	5 Mitigation
6 Reliance on open-source data	7 Missing classified procurement records	8 Conservative estimates, triangulation
9 Non-existence of classified training records	0 Limited simulations exposure data	1 Use institutional reports, and OSINT
2 In-built bias within self-reported measurements	3 Possibility of overstating training hours	4 Sensitivity analyses, cross-validation
Stylized models for learning processes	Simplification of the operational dynamics	Scenario bounding, robustness checks

Source: The table is generated by the authors

Appendix E: Sensitivity Analysis (Cost Ratios)

Attacker Cost ($)	Defender Cost ($)	Cost ratio
1,500	30,000	20:1
2,000	50,000	25:1
3,000	60,000	20:1

Source: The table is generated by the authors