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Artificial Intelligence-Enhanced Simulation for Air and Missile Defense Operations: A Systematic Review of Modeling, Decision Support, and Adaptive Analysis

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ABSTRACT

The rapid evolution of aerial threats, the increasing heterogeneity of sensor data, and the growing complexity of networked defense architectures have created substantial demands for more intelligent, adaptive, and interoperable simulation environments. Traditional simulation approaches remain essential for representing events, entities, system interactions, and distributed architectures; however, their ability to accommodate dynamic uncertainty, heterogeneous data, evolving threat representations, and human–machine decision processes is increasingly constrained. This systematic review examines the development of artificial intelligence (AI)-enhanced simulation for air and missile defense operations, with particular attention to modeling architectures, decision-support mechanisms, real-time data fusion, digital twins, adaptive simulation, and human–AI collaboration. The review synthesizes conventional approaches, including event-driven simulation, High Level Architecture (HLA), agent-based modeling, distributed interactive simulation, and mixed-reality simulation, and evaluates how machine learning, deep learning, reinforcement learning, predictive analytics, and other AI techniques can augment these approaches. Particular attention is given to five persistent challenges: data quality and heterogeneity, model fidelity and uncertainty, interoperability, validation and verification, and explainability of AI-supported outputs. The review further identifies digital-twin-enabled simulation, adaptive multi-agent architectures, real-time data assimilation, uncertainty-aware AI, explainable decision support, and quantum-assisted optimization as important research directions. The analysis suggests that the future of air and missile defense simulation is unlikely to depend on a single computational paradigm. Rather, progress will require integrated architectures in which conventional modeling and simulation provide physical and logical consistency, AI provides adaptive analytical capabilities, and human decision-makers remain responsible for interpreting and validating simulation-supported recommendations. The resulting paradigm can be characterized as an AI-enhanced, data-centric, adaptive, interoperable, and human-centered simulation ecosystem.

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INTRODUCTION

The contemporary air and missile defense environment is characterized by increasing technological diversity, uncertainty, and information density. The evolution of aerial platforms, unmanned systems, complex trajectories, electronic interference, autonomous systems, and networked sensing has transformed the analytical requirements imposed on defense simulation. Consequently, simulation is no longer limited to reproducing predefined scenarios; it increasingly functions as an analytical environment for exploring alternative states, evaluating system behavior, examining uncertainty, and supporting human decision-making.

Modeling and simulation have long been employed for training, experimentation, system development, mission rehearsal, and analysis. NATO, for example, identifies modeling and simulation as an important component of research and development, collective training, experimentation, wargaming, and mission rehearsal, while emphasizing interoperability and standards-based architectures.

Traditional simulation architectures, however, encounter several limitations when applied to highly dynamic environments. Static or predetermined models may struggle to represent rapidly changing conditions. Large heterogeneous datasets may exceed the capacity of conventional analytical workflows. Furthermore, the interaction between multiple autonomous or semi-autonomous entities creates nonlinear behaviors that are difficult to represent through deterministic rules alone.

Artificial intelligence offers a potential solution to some of these limitations. Machine learning can identify patterns in large datasets, deep learning can model complex nonlinear relationships, reinforcement learning can investigate sequential decision processes, and AI-assisted analytics can support adaptive scenario generation and prediction. Nevertheless, the introduction of AI does not automatically guarantee better simulation. AI models may themselves introduce uncertainty, bias, data dependence, opacity, computational costs, and maintenance challenges. Research on machine-learning systems has demonstrated that operational ML systems can accumulate substantial technical debt through data dependencies, feedback loops, configuration problems, and changes in the external environment.

Therefore, the fundamental research question is not simply whether AI can be introduced into simulation, but **how AI can be integrated with established modeling and simulation architectures while maintaining validity, interpretability, interoperability, adaptability, and human oversight**.

The present review addresses this question by examining the evolution from conventional simulation toward AI-enhanced simulation and by identifying the major technological and methodological gaps that must be addressed before AI-enabled simulation can become a reliable analytical framework.

2. Review Methodology

2.1 Review objective

This study adopts a systematic-review framework to organize and synthesize research concerning AI-enhanced simulation for air and missile defense operations. The review focuses on the intersection of five domains:

1. Modeling and simulation;
2. Artificial intelligence and machine learning;
3. Decision-support systems;
4. Digital twins and real-time data fusion;
5. Adaptive and human-centered simulation.

The objective is not to evaluate individual weapon systems or operational tactics, but to examine the computational and analytical methodologies used to construct, integrate, validate, and adapt simulation environments.

2.2 Literature identification

The literature framework was organized around combinations of terms including:

- "air and missile defense simulation";
- "artificial intelligence simulation";
- "AI-enhanced decision support";
- "agent-based modeling";
- "distributed simulation";
- "High Level Architecture";
- "digital twin simulation";
- "real-time data fusion";
- "adaptive simulation";
- "explainable AI";
- "human–AI collaboration";
- "model validation and uncertainty."

Foundational simulation literature was considered alongside contemporary literature addressing AI, digital twins, adaptive modeling, and interoperable simulation architectures.

2.3 Inclusion criteria

Studies were considered relevant when they addressed at least one of the following:

- computational simulation;
- AI-based modeling;
- simulation interoperability;

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- decision-support systems;
- digital twins;
- real-time data assimilation;
- adaptive simulation;
- agent-based systems;
- human–AI interaction;
- simulation verification and validation.

Foundational studies were retained when they established important theoretical or architectural concepts that remain relevant to contemporary simulation.

2.4 Analytical framework

The reviewed literature was classified into four analytical layers:

Layer 1 – Physical and environmental modeling

Representation of systems, entities, environments, sensors, and physical processes.

Layer 2 – Computational simulation

Event-driven, distributed, agent-based, HLA, and mixed-reality architectures.

Layer 3 – Artificial intelligence

Machine learning, deep learning, reinforcement learning, prediction, anomaly detection, and adaptive modeling.

Layer 4 – Decision and human interaction

Decision support, explainability, human–AI collaboration, cognitive modeling, and uncertainty communication.

This layered framework enables the transition from conventional simulation toward AI-enhanced simulation to be analyzed systematically.

3. Conceptual Foundations of AI-Enhanced Simulation

3.1 From conventional simulation to intelligent simulation

Traditional simulation attempts to reproduce the behavior of a real or conceptual system according to predefined mathematical, physical, logical, or statistical rules. Its strength lies in transparency and controllability: researchers can explicitly define assumptions, parameters, relationships, and boundary conditions.

AI-enhanced simulation introduces a second source of intelligence: **data-driven learning**.

Instead of relying exclusively on predefined rules, the simulation may learn patterns from historical or synthetic datasets. This produces a hybrid architecture:

Physics/Rules + Simulation + Data + AI + Human Judgment

The combination is potentially more powerful than any individual component.

However, AI should not automatically replace deterministic or physics-based models. In high-consequence environments, hybrid modeling is generally more defensible because physical constraints can restrict unrealistic AI outputs while AI can approximate complex relationships that are difficult to formulate analytically.

4. Major Challenges in AI-Enhanced Air and Missile Defense Simulation

4.1 Data quality, heterogeneity, and uncertainty

Data constitute the foundation of AI-enhanced simulation. The quality of the simulation therefore depends not only on algorithmic performance but also on the quality and representativeness of its inputs.

Simulation environments may integrate heterogeneous data originating from sensors, environmental models, historical datasets, synthetic scenarios, and system logs. These datasets may differ in temporal resolution, spatial resolution, accuracy, uncertainty, and semantic structure.

Three problems are particularly important:

Completeness: critical variables may be unavailable.

Consistency: different sources may describe the same phenomenon using incompatible representations.

Timeliness: information may become outdated before it is incorporated into a simulation.

AI systems can partially mitigate these challenges through data fusion, anomaly detection, imputation, and probabilistic modeling. Nevertheless, AI cannot eliminate uncertainty originating from poor or incomplete data.

Accordingly, future systems should represent uncertainty explicitly rather than treating every input as a precise observation.

4.2 Model fidelity and computational complexity

Model fidelity describes the extent to which a simulation adequately represents the characteristics of the system under investigation.

High-fidelity models may provide detailed representations but require substantial computational resources. Low-fidelity models can execute more rapidly but may omit relevant mechanisms.

AI introduces a third possibility: **adaptive fidelity**.

An AI-enhanced simulator could dynamically determine which components require detailed modeling and which can be represented through reduced-order or surrogate models.

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This creates the possibility of a variable-fidelity architecture in which computational resources are allocated according to analytical importance.

4.3 Uncertainty propagation

Uncertainty can enter the simulation through:

- input data;
- model parameters;
- environmental assumptions;
- incomplete information;
- stochastic processes;
- AI model predictions;
- human decisions.

An important research gap is therefore the development of **uncertainty-aware AI simulation**, in which the system communicates not only a prediction but also an estimate of confidence or uncertainty.

Instead of presenting:

“The predicted outcome is X.”

the system should ideally communicate:

“X is the most probable outcome under the specified assumptions, with uncertainty associated with data quality, model parameters, and scenario variability.”

This distinction is fundamental for responsible decision support.

4.4 Interoperability

Modern simulation rarely operates as a single isolated program. Multiple simulators, databases, analytical tools, and synthetic environments may need to exchange information.

NATO documentation emphasizes the importance of standards for interoperability and reuse in modeling and simulation. Its standards ecosystem includes HLA, distributed simulation processes, and related interoperability standards.

The challenge becomes greater when AI components are added because AI models require additional information concerning:

- data schemas;
- model versions;
- training datasets;
- inference interfaces;

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- uncertainty representations;
- provenance;
- validation status.

Consequently, future interoperability standards must evolve from simple data exchange toward **semantic interoperability for AI-enabled simulation**.

4.5 Verification, validation, and credibility

AI-enhanced simulation raises a fundamental question:

How can researchers demonstrate that an adaptive model remains trustworthy when its behavior changes after learning?

Conventional simulation validation typically examines whether the model adequately represents the intended real-world system.

AI adds another dimension: model behavior may depend on training data and may change as new data are incorporated.

Therefore, future validation frameworks should evaluate:

1. physical validity;
2. logical validity;
3. statistical validity;
4. AI model performance;
5. robustness;
6. uncertainty;
7. behavior under distribution shift;
8. explainability;
9. human usability.

Simulation credibility should consequently be understood as a continuous lifecycle process rather than a one-time certification event.

5. Conventional Simulation Approaches

5.1 Event-Driven Simulation

Event-Driven Simulation (EDS) represents a system through discrete events that alter its state.

The method is particularly useful when system behavior can be described through sequences of state transitions. Instead of continuously calculating every variable, the simulator advances from one significant event to another.

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Its advantages include:

- computational efficiency;
- explicit event sequencing;
- causal representation;
- flexibility in scenario construction.

Its limitation is that highly complex environments may contain a very large number of interacting events.

AI can enhance EDS through intelligent event prioritization, anomaly detection, predictive event generation, and adaptive scheduling.

The resulting architecture can be described as:

Event Detection → AI Prediction → Event Prioritization → Simulation Update → Decision Support

5.2 High Level Architecture

High Level Architecture (HLA) was developed to enable interoperability among different simulation components. HLA provides a framework through which multiple simulation applications, or federates, can participate in a federation.

The architecture remains important because modern simulation environments often require integration of heterogeneous components.

NATO continues to recognize HLA and related standards within its modeling and simulation interoperability framework.

The future challenge is to transform HLA-based architectures from simple interoperable simulation federations into **AI-enabled federations**.

Such systems could allow different AI models to operate as specialized federates, while exchanging standardized information with conventional simulators.

5.3 Agent-Based Modeling

Agent-Based Modeling (ABM) represents a system through autonomous agents that possess individual rules, states, objectives, and interaction mechanisms.

The theoretical foundations of intelligent agents emphasize autonomy, interaction, and agent architectures.

ABM is especially useful for examining emergent behavior because system-level patterns can arise from interactions among individual agents.

AI can significantly expand ABM by replacing static behavioral rules with adaptive agents.

For example, an AI-enabled agent may:

- learn from previous simulations;
- modify its behavior;
- respond to environmental changes;
- evaluate alternative actions;
- interact with other intelligent agents.

This leads to **multi-agent AI simulation**, one of the most promising directions for future research.

5.4 Distributed Interactive Simulation

Distributed Interactive Simulation (DIS) allows multiple simulation entities to interact through a distributed computational environment.

Its major advantages include scalability and real-time interaction.

However, distributed simulation introduces challenges concerning:

- synchronization;
- communication latency;
- data consistency;
- network reliability;
- computational heterogeneity.

AI can assist by predicting communication requirements, detecting anomalous simulation states, and dynamically allocating computational resources.

5.5 Mixed-Reality Simulation

Mixed-reality simulation combines elements of physical and virtual environments.

Its principal contribution is human immersion.

Mixed-reality environments can support:

- operator training;
- human decision experiments;
- interface evaluation;
- workload assessment;
- human–AI interaction studies.

The future importance of MRS lies less in visual realism alone and more in the ability to evaluate **how humans interact with AI-supported simulation systems**.

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6. AI-Enhanced Simulation

6.1 Machine Learning for Simulation

Machine learning can be used in several ways:

1. **Surrogate modeling** – replacing computationally expensive models with faster approximations.
2. **Prediction** – estimating future system states.
3. **Classification** – categorizing simulated events.
4. **Anomaly detection** – identifying unusual system behavior.
5. **Parameter estimation** – optimizing model parameters.
6. **Adaptive modeling** – updating the model as new information becomes available.

The most promising approach is therefore not "AI instead of simulation," but:

AI + Simulation

where each technology compensates for the limitations of the other.

6.2 Deep Learning

Deep learning is particularly suitable for high-dimensional datasets.

Its potential applications include:

- complex pattern recognition;
- time-series prediction;
- image-based classification;
- representation learning;
- nonlinear surrogate modeling.

However, deep neural networks may be difficult to interpret.

This is particularly important in high-consequence decision environments, where the ability to explain the reasoning behind an AI output can be as important as predictive accuracy.

6.3 Reinforcement Learning

Reinforcement Learning (RL) differs from conventional supervised learning because an agent learns through interaction with an environment and receives rewards or penalties associated with its behavior.

Simulation provides an attractive environment for RL because the model can generate large numbers of synthetic experiences without requiring equivalent real-world experimentation.

At a methodological level, RL can therefore be used to explore policy spaces and adaptive decision processes.

However, RL simulations must be carefully designed because an incorrectly defined reward function can produce behavior that optimizes the mathematical objective without satisfying the broader analytical objective.

7. AI-Enhanced Decision Support

Decision-support systems transform simulation outputs into information that can assist human analysts and decision-makers.

Traditional systems may display:

- predicted states;
- statistical outputs;
- scenario comparisons;
- performance metrics.

AI-enhanced systems can additionally identify patterns and prioritize information.

A conceptual architecture is:

Data → Simulation → AI Analysis → Uncertainty Estimation → Explanation → Human Decision

The inclusion of an explanation layer is essential.

A high-performing model that cannot communicate why its recommendation emerged may be unsuitable for high-stakes applications.

Research on interpretable machine learning has emphasized the limitations of relying exclusively on post-hoc explanations for black-box systems and has argued for greater attention to inherently interpretable models in high-stakes decision settings.

8. Real-Time Data Fusion and Dynamic Simulation

Real-time simulation requires continuous updating.

The architecture can be conceptualized as:

Data Acquisition → Data Fusion → State Estimation → Model Update → AI Analysis → Simulation → Decision Support

Data fusion integrates multiple sources to construct a more coherent representation of the simulated environment.

AI can support this process by:

- identifying inconsistencies;

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- estimating missing information;
- detecting anomalies;
- weighting sources;
- predicting short-term changes;
- updating model parameters.

The principal research challenge is latency. A simulation may be highly accurate but practically less useful if its results arrive too late to support the relevant decision cycle.

This creates a trade-off between:

accuracy – computational complexity – latency.

AI-enhanced architectures should therefore optimize these three dimensions simultaneously.

9. Digital Twin-Enabled Simulation

Digital twins represent a major evolution beyond conventional simulation.

A digital twin maintains a computational representation of a physical system and updates it using information from the corresponding real-world system.

The growing literature on digital twins and AI-based decision support demonstrates their potential for real-time monitoring, prediction, and adaptive analysis.

For air and missile defense simulation research, a generalized digital-twin architecture can contain:

1. physical system representation;
2. data acquisition;
3. data integration;
4. simulation model;
5. AI analytical layer;
6. synchronization mechanism;
7. decision-support interface.

The major advantage is continuity.

Traditional simulation is often conducted at a particular point in time, whereas digital-twin-enabled simulation can continuously update its representation as the underlying system changes.

Nevertheless, digital twins face important challenges concerning data availability, synchronization, model fidelity, cybersecurity, interoperability, and computational cost.

10. Adaptive Simulation

Adaptive simulation represents a transition from static models to models capable of changing their structure or parameters.

An adaptive system can:

- update parameters;
- modify model fidelity;
- introduce new behavioral patterns;
- select alternative algorithms;
- incorporate new data;
- identify changes in the environment.

The concept is particularly important when the system under study evolves faster than the simulation development cycle.

However, adaptation must be controlled.

A model that changes without adequate validation can become less trustworthy over time.

Consequently, future adaptive systems should include **continuous validation gates**.

11. Multi-Agent AI Simulation

The combination of ABM and AI creates an important research direction.

Instead of predefined agents, AI-enabled agents can learn from simulated experience.

The resulting architecture may include:

- autonomous learning agents;
- heterogeneous objectives;
- incomplete information;
- communication constraints;
- dynamic environments;
- emergent system behavior.

This enables researchers to investigate how complex system-level patterns arise from local interactions.

Nevertheless, multi-agent learning introduces challenges related to stability, convergence, interpretability, computational cost, and emergent behaviors that may not have been explicitly programmed.

Therefore, multi-agent AI simulation should be viewed as an analytical research tool rather than a deterministic predictor of future behavior.

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12. Human–AI Collaboration

A major weakness in many AI-centered approaches is the assumption that better algorithms automatically generate better decisions.

In reality, decision quality depends on the interaction between:

information + algorithm + human cognition + organizational context.

Human operators may misinterpret AI outputs, overtrust automated recommendations, or ignore useful information because of excessive system complexity.

Situation-awareness research has long emphasized the importance of attention, workload, stress, mental models, and system complexity in dynamic decision-making.

Therefore, future simulation systems should incorporate human-in-the-loop experimentation.

The objective should not be to eliminate human decision-makers, but to determine the most effective division of responsibilities between humans and AI.

13. Explainable and Trustworthy AI

Explainability should be integrated into the simulation architecture rather than added after the AI model has been developed.

An explainable simulation system should ideally answer:

- What information influenced the prediction?
- Which variables were most important?
- How sensitive is the result to input changes?
- What uncertainty exists?
- Under which assumptions does the result remain valid?
- When should the human decision-maker distrust the model?

This suggests that future simulation outputs should contain at least three components:

Prediction + Confidence + Explanation

Such a structure can improve analytical transparency and support appropriate human oversight.

14. Cross-Domain and Interoperable Simulation

Modern defense simulation increasingly requires interaction among multiple domains and heterogeneous computational systems.

The technological challenge is therefore not simply increasing computational power but ensuring that models can communicate.

NATO's current modeling and simulation work emphasizes interoperability, standards, reusable simulation components, and distributed synthetic environments.

Future architectures should therefore combine:

- HLA;
- distributed simulation;
- cloud computing;
- edge computing;
- standardized data models;
- AI services;
- digital twins.

The resulting environment can be described as **Simulation as a Service (SimaaS)** or **Modeling and Simulation as a Service (MSaaS)**.

NATO has explicitly explored data-centric, web-enabled, modular synthetic environments and M&S-as-a-Service concepts.

15. Quantum-Assisted Simulation

Quantum computing represents a potentially important long-term direction.

However, claims regarding immediate quantum superiority should be treated cautiously.

Quantum technologies may eventually contribute to selected optimization and computational problems, but practical quantum advantage depends on algorithm suitability, hardware maturity, error correction, and problem structure.

Accordingly, the most defensible research direction is **quantum-assisted optimization**, rather than assuming that complete simulation environments will simply migrate to quantum computers.

Potential research areas include:

- optimization;
- combinatorial search;
- parameter estimation;
- selected machine-learning tasks;
- uncertainty analysis.

This field remains emerging and requires substantial validation before operational claims can be made.

16. Cognitive and Human-Centered Simulation

The future of simulation should increasingly account for human cognitive processes.

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A purely technical simulation may reproduce physical and computational interactions while failing to represent:

- workload;
- attention;
- uncertainty perception;
- trust;
- fatigue;
- decision bias;
- information overload.

Cognitive simulation can therefore complement physical and computational modeling.

Rather than attempting to model human psychology perfectly, future systems should identify measurable cognitive variables that influence decision quality.

This creates a broader framework:

Physical Environment + Computational Environment + Information Environment + Human Cognitive Environment

17. Future Research Directions

17.1 AI-native simulation architectures

Future simulation platforms should be designed with AI integration from the beginning rather than adding AI modules to legacy architectures.

17.2 Hybrid physics–AI models

Combining physical constraints with machine learning can improve generalization and reduce physically implausible outputs.

17.3 Uncertainty-aware AI

AI models should communicate confidence intervals, probabilistic estimates, or alternative scenario distributions where appropriate.

17.4 Continuous validation

Adaptive models require continuous verification and validation rather than one-time certification.

17.5 Digital twin ecosystems

Digital twins should evolve from individual system representations into interoperable networks of interconnected models.

17.6 Human-centered AI

Human expertise should remain an integral component of the simulation architecture.

17.7 Explainability by design

Explainability should be incorporated during model development rather than added after deployment.

17.8 AI model governance

Future systems require version control, dataset provenance, model documentation, performance monitoring, and lifecycle management.

This is particularly important because ML systems can accumulate hidden technical debt and become unreliable as their data and operating environments change.

18. Integrated Conceptual Framework

Based on the literature reviewed, this study proposes an integrated conceptual framework for AI-enhanced simulation:

Data Layer

↓

Data Fusion and Uncertainty Management

↓

Simulation Layer
Event-driven + HLA + ABM + Distributed Simulation + Digital Twin

↓

AI Layer
Machine Learning + Deep Learning + Reinforcement Learning + Predictive Analytics

↓

Adaptive Analysis Layer
Dynamic Modeling + Scenario Generation + Uncertainty Analysis

↓

Decision-Support Layer
Prediction + Explanation + Confidence + Alternatives

↓

Human Decision Layer

↓

Feedback and Continuous Learning

This architecture creates a closed analytical loop:

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Observe → Model → Simulate → Learn → Adapt → Explain → Decide → Update

The key conceptual contribution is that AI is not treated as an independent component but as an **intelligence layer embedded within the broader modeling and simulation lifecycle**.

19. Discussion

The reviewed literature indicates that the evolution of air and missile defense simulation is not simply a technological transition from conventional computing to AI. Rather, it represents a transformation in the philosophy of simulation.

Traditional simulation emphasizes predefined models, while AI-enhanced simulation introduces adaptive learning.

Traditional simulation tends to separate model development from execution, whereas digital twins seek continuous synchronization.

Traditional decision-support systems primarily present information, whereas AI-enhanced systems can interpret large datasets and generate analytical recommendations.

Traditional interoperability focuses mainly on data and system connectivity, whereas future interoperability must also include semantic compatibility, AI-model compatibility, uncertainty representation, and model provenance.

The most important conclusion is therefore that future simulation systems should be **hybrid rather than purely AI-driven**.

Physics-based and rule-based models provide interpretability and constraints. AI contributes adaptability and pattern recognition. Distributed simulation provides scalability. Digital twins provide continuity. Human-centered design provides contextual judgment.

The integration of these elements can produce a more robust simulation ecosystem.

At the same time, several limitations remain. First, AI performance is highly dependent on data quality. Second, simulation outputs cannot automatically be interpreted as predictions of real-world events. Third, adaptive models may change their behavior as new data become available. Fourth, interoperability remains a technical and organizational challenge. Finally, the complexity of AI-enhanced architectures may itself create new sources of uncertainty.

Consequently, the objective should not be to construct the most complicated simulation possible, but rather to construct a simulation whose **complexity is justified by the analytical question being addressed**.

20. Conclusions

This systematic review examined the development of AI-enhanced simulation for air and missile defense operations, focusing on modeling architectures, decision support, adaptive analysis, digital twins, real-time data fusion, and human–AI collaboration.

The analysis demonstrates that conventional approaches such as event-driven simulation, HLA, agent-based modeling, distributed interactive simulation, and mixed-reality simulation remain fundamental components of modern simulation ecosystems. Their continued relevance is reinforced by the importance of interoperability, reuse, distributed architectures, and standardized simulation environments. NATO's current modeling and simulation activities similarly emphasize interoperable and reusable synthetic environments and the continued evolution of simulation standards.

Artificial intelligence expands these capabilities by enabling adaptive modeling, predictive analysis, intelligent agents, real-time data interpretation, and decision-support functions. However, AI should not be considered a replacement for established simulation methodologies. The most promising direction is the development of hybrid architectures that combine physical and rule-based modeling with machine learning and adaptive analytical techniques.

Digital twins provide another major opportunity by connecting simulation models with continuously updated representations of real-world systems. AI can further enhance these environments by supporting anomaly detection, prediction, model updating, and decision analysis.

At the same time, the deployment of AI-enhanced simulation introduces significant challenges. Data quality, uncertainty, model validity, explainability, interoperability, cybersecurity, computational cost, and human–AI trust must be addressed as integral elements of the simulation lifecycle.

Future research should therefore concentrate on five priorities: **AI-native simulation architectures, uncertainty-aware adaptive modeling, interoperable digital twins, explainable decision support, and human-centered AI**.

Ultimately, the future simulation paradigm can be characterized as:

data-centric, AI-enhanced, adaptive, interoperable, uncertainty-aware, and human-centered.

Such a paradigm has the potential to transform simulation from a predominantly static analytical tool into a continuously evolving environment for experimentation, assessment, training, decision support, and system development. The central scientific challenge is not simply to make simulation more intelligent, but to make intelligent simulation **credible, interpretable, adaptive, and scientifically defensible**.

Ethical Considerations

Not applicable. This study did not require ethical approval because it does not include human or animal subjects and does not involve any personal or sensitive data.

List of Abbrevations:

(AI): artificial intelligence; (HLA): High Level Architecture;(EDS) Event-Driven Simulation ; (ABM) : Agent-Based Modeling; (DIS) : Distributed Interactive Simulation; (RL) : Reinforcement Learning;

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Declaration of generative AI and AI-assisted technologies in the writing process

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