ISSN: 2977-0041

Review Article

Journal of Material Sciences and Engineering Technology

System-Level Optimization of Multi-Layer Defense Coverage Integrating Artificial Intelligence Network Efficiency and Non-Terrestrial Communication for Global Interception Effectiveness

Shankar Subramanian Iyer[1*], Rajesh Arora[2], Sangeeta Malhotra[3] and Brinitha Raji[4]

[1]*Faculty, Westford University College, Al Khan, Sharjah, UAE*

[2]*Prof, Westford University College, Al Khan, Sharjah, UAE*

[3]*Assessor /Trainer PWC Academy*

[4]*Faculty, Global Business Studies, DKP, Dubai*

[*]Corresponding author

Shankar Subramanian Iyer, Westford University College, Al Khan, Sharjah, UAE.

Received: April 10, 2026; **Accepted:** April 17, 2026; **Published:** April 24, 2026

ABSTRACT

Background: Modern defense systems face unprecedented challenges from hypersonic threats, drone swarms, and cyber-physical warfare, necessitating a transition from isolated platforms to network-centric, artificial intelligence-enabled ecosystems. Traditional coverage models are insufficient for addressing multi-domain threats requiring optimized spatial deployment and real-time coordination [1,2].

Methods: This study develops an integrated system-level framework grounded in Systems Theory and Complex Adaptive Systems to evaluate multi-layer defense coverage optimization. A mixed-method approach combining Structural Equation Modeling with qualitative expert interviews was employed. The quantitative phase involved 200 defense, telecommunications, and artificial intelligence experts completing a 35-item Likert scale questionnaire measuring seven constructs: System Deployment Density, Network-Centric Integration, Technology Capability, Communication Infrastructure, Network Efficiency, Coverage Optimization, and Defense System Effectiveness. Mathematical modeling incorporated spherical coverage calculations and hexagonal grid optimization achieving 0.907 efficiency [3,4].

Results: The conceptual model demonstrates that system deployment density, network-centric integration, technology capability, and communication infrastructure influence defense system effectiveness through mediating pathways of network efficiency and coverage optimization. Mathematical analysis indicates approximately 1,000 optimally deployed systems can achieve global coverage across three layered defense zones: outer layer (400+ km), mid layer (100–300 km), and inner layer (<100 km). Threat complexity moderates the relationship between coverage optimization and system effectiveness [5,6].

Conclusion: This research provides a comprehensive framework integrating artificial intelligence-driven coordination, non-terrestrial communication networks, and spatial optimization strategies for next-generation defense architectures. The findings offer both theoretical advancement in defense systems modeling and practical deployment guidelines for maximizing interception probability while minimizing coverage redundancy [7,8].

List of Abbreviations

AI	:	Artificial Intelligence
AMOS	:	Analysis of Moment Structures
AVE	:	Average Variance Extracted
CAS	:	Complex Adaptive Systems
CI	:	Communication Infrastructure

Citation: Shankar Subramanian Iyer, Rajesh Arora, Sangeeta Malhotra, Brinitha Raji. System-Level Optimization of Multi-Layer Defense Coverage Integrating Artificial Intelligence Network Efficiency and Non-Terrestrial Communication for Global Interception Effectiveness. J Mat Sci Eng Technol. 2026. 4(2): 1-13.

DOI: doi.org/10.61440/JMSET.2026.v4.111

CO	:	Coverage Optimization
DSE	:	Defense System Effectiveness
HTMT	:	Heterotrait-Monotrait Ratio
IV	:	Independent Variable
NCI	:	Network-Centric Integration
NE	:	Network Efficiency
SDD	:	System Deployment Density
SEM	:	Structural Equation Modeling
SmartPLS	:	Partial Least Squares Structural Equation Modeling Software
TAM	:	Technology Acceptance Model
TC	:	Technology Capability

Keywords: Defense Systems Optimization, Network-Centric Warfare, Artificial Intelligence Integration, Spatial Deployment Strategies, Non-Terrestrial Communication, Coverage Optimization

Introduction

The contemporary security environment is characterized by rapidly evolving threats that challenge traditional defense paradigms [1]. Hypersonic weapons capable of exceeding Mach 5, autonomous drone swarms operating in coordinated formations, and sophisticated cyber-physical attacks targeting critical infrastructure have rendered conventional point-defense architectures inadequate [2,3]. The transition from isolated, platform-centric defense systems to integrated, network-centric ecosystems represent a fundamental paradigm shift in modern military strategy [4,5].

Network-centric warfare, enabled by advances in artificial intelligence (AI), satellite communication, and sensor fusion, offers unprecedented opportunities for enhancing defense system effectiveness [6,7]. AI-driven decision support systems can process vast quantities of sensor data in real time, enabling rapid threat identification and interception coordination that exceeds human cognitive capabilities [8,9]. Non-terrestrial communication networks, including satellite constellations and high-altitude platforms, provide resilient connectivity that supports distributed defense architectures across geographically dispersed areas [10,11].

Despite these technological advances, a critical gap exists in the literature regarding the system-level optimization of multi-layer defense coverage [12]. Existing research tends to focus on individual components — radar performance, interceptor effectiveness, or communication protocols — without adequately addressing the emergent properties that arise from system integration [13,14]. Furthermore, the spatial deployment of defense systems, which fundamentally determines coverage efficiency and gap minimization, has received insufficient attention in the context of AI-enabled architectures [15].

This research addresses this gap by developing a comprehensive framework that integrates spatial optimization theory with network-centric defense principles. Grounded in Systems Theory and Complex Adaptive Systems (CAS), the study investigates how system deployment density (SDD), network-centric integration (NCI), technology capability (TC), and communication infrastructure (CI) influence defense system effectiveness (DSE) through the mediating mechanisms of network efficiency (NE) and coverage optimization (CO) [16,17]. The moderating role of threat complexity is also examined to understand boundary conditions of the proposed relationships [18].

The central research question is: How can multi-layer defense systems be optimized for maximum coverage and interception efficiency through the integration of AI-driven network coordination, non-terrestrial communication, and spatial deployment strategies? To address this question, a mixed-method approach combining Structural Equation Modeling (SEM) with qualitative expert interviews is employed, supplemented by mathematical modeling of spatial coverage geometries [19-21].

This paper makes several contributions to the field. First, it develops an integrated theoretical framework connecting spatial optimization with network-centric defense principles. Second, it provides empirically testable hypotheses linking system configuration variables to effectiveness outcomes. Third, it offers mathematical models for calculating optimal deployment configurations. Fourth, it provides practical guidelines for defense planners and systems engineers designing next-generation multi-layer architectures [22,23].

Literature Review

Multi-Layer Defense Systems

Multi-layer defense, also termed defense-in-depth, represents a strategic architecture in which multiple overlapping defensive layers provide redundant engagement opportunities against incoming threats [24,25]. The layered approach ensures that if one defensive tier is saturated or defeated, subsequent tiers provide additional interception opportunities [26]. Historical implementations include the Patriot missile system integrated with THAAD (Terminal High Altitude Area Defense) and Aegis naval systems, creating interlocking coverage zones across different altitude and range envelopes [27,28].

Contemporary multi-layer architectures extend beyond kinetic interceptors to include directed energy weapons, electronic warfare systems, and cyber defense capabilities operating in an integrated, networked configuration [29,30]. The effectiveness of such systems depends critically on the coordination architecture enabling seamless handoff between layers and optimal resource allocation across engagement opportunities [31,32].

Artificial Intelligence in Defense Systems

Artificial intelligence applications in defense systems have expanded dramatically, encompassing threat classification, trajectory prediction, resource allocation, and engagement sequencing [33,34]. Machine learning algorithms, particularly deep neural networks and reinforcement learning approaches, have demonstrated superior performance compared to rule-based systems in complex, dynamic threat environments [35,36]. The integration of AI into command-and-control architectures enables autonomous or semi-autonomous engagement decisions at speeds exceeding human reaction times [37,38].

Swarm intelligence algorithms, inspired by biological systems such as ant colonies and bird flocking, offer promising approaches for coordinating distributed defense assets against coordinated threat swarms [39,40]. These algorithms enable emergent coordination behaviors without centralized control, enhancing system resilience against decapitation attacks targeting command nodes [41,42].

Network-Centric Warfare

Network-centric warfare (NCW) represents a military doctrine emphasizing the power of networked forces over platform-centric approaches [43,44]. The NCW framework posits that superior information sharing, enabled by robust communication networks, translates into enhanced situational awareness and coordinated action that provides decisive military advantage [45,46]. Empirical studies have demonstrated that network-enabled forces achieve significantly higher engagement effectiveness compared to isolated platforms operating with limited information sharing [47,48].

The theoretical underpinnings of NCW draw from network theory, particularly the concepts of network topology, information diffusion, and emergent collective behavior [49,50]. Small-world network properties, characterized by high clustering and short path lengths, have been identified as optimal for military communication architectures balancing connectivity with resilience [51,52].

Spatial Optimization and Coverage Models

Spatial optimization of sensor and weapon system deployment draws from operations research, computational geometry, and geographic information systems [53,54]. Coverage problems, seeking to maximize the area monitored by a given number of sensors, represent a class of combinatorial optimization problems with well-studied algorithmic solutions [55,56]. Hexagonal tessellation has been identified as the optimal geometric arrangement for area coverage, achieving 90.7% efficiency compared to square grid arrangements [57,58].

Voronoi diagrams and their dual Delaunay triangulations provide mathematical frameworks for optimizing sensor placement relative to threat approach corridors and protected asset locations [59,60]. multi-objective optimization approaches balance competing objectives including coverage maximization, redundancy minimization, and survivability enhancement [61,62].

Non-Terrestrial Communication Networks

Non-terrestrial networks (NTN), encompassing satellite systems, high-altitude platform stations (HAPS), and unmanned aerial vehicles (UAV), provide communication infrastructure for defense systems operating in contested or denied environments where terrestrial networks may be degraded [63,64]. Low Earth Orbit (LEO) satellite constellations, exemplified by commercial systems such as Starlink and OneWeb, offer global coverage with latency suitable for near-real-time command and control applications [65,66].

The integration of NTN with terrestrial defense networks creates hybrid architectures combining the resilience of space-based assets with the bandwidth and latency advantages of ground-based systems [67,68]. Emerging 5G non-terrestrial network standards provide standardized interfaces enabling seamless integration of space, aerial, and ground communication layers [69,70].

Theoretical Foundations

Systems Theory, originating with von Bertalanffy's General Systems Theory, provides a holistic framework for analyzing defense systems as integrated wholes whose properties emerge from component interactions rather than individual capabilities [71-73]. Complex Adaptive Systems theory extends this perspective by emphasizing adaptation, self-organization, and emergent behavior in response to environmental changes [74,75]. These theoretical lenses are particularly appropriate for analyzing modern defense architectures characterized by high component interdependency and dynamic threat environments [76,77].

The Technology Acceptance Model (TAM) and its extensions provide frameworks for understanding the adoption and effective utilization of AI systems within defense organizations [78-80]. Network Theory contributes concepts of centrality, redundancy, and robustness applicable to communication architecture design [81,82]. Together, these theoretical foundations provide a multi-level analytical framework spanning individual technology adoption, organizational processes, and system-level architecture [83,84].

Research Gaps

Despite extensive research on individual components of defense system optimization, several critical gaps remain in the literature. First, integrated frameworks connecting spatial deployment optimization with network-centric performance metrics are lacking [85,86]. Second, the mediating mechanisms through which communication infrastructure and integration capabilities translate to system effectiveness remain underspecified [87,88]. Third, empirical validation of theoretical optimization models using expert survey data and SEM has been limited [89,90]. This study addresses these gaps by developing and testing an integrated conceptual model grounded in multiple theoretical traditions [91,92].

Conceptual Model and Hypotheses

The conceptual framework (Figure 1) integrates four independent variables — System Deployment Density (SDD), Network-Centric Integration (NCI), Technology Capability (TC), and Communication Infrastructure (CI) — with two mediating variables — Network Efficiency (NE) and Coverage Optimization (CO) — and one dependent variable, Defense System Effectiveness (DSE). Threat Complexity serves as a moderating variable influencing the CO–DSE relationship [93,94].

Direct Effect Hypotheses

H1: System Deployment Density has a significant positive effect on Coverage Optimization. Higher deployment density reduces spatial gaps and increases the probability of continuous coverage across the defended area [95,96].

H2: Network-Centric Integration has a significant positive effect on Network Efficiency. Greater integration enables faster data sharing, reduced latency in coordination, and more effective resource allocation [97,98].

H3: Technology Capability has a significant positive direct effect on Defense System Effectiveness. Advanced radar, interceptor, and AI technologies directly enhance the probability of successful threat neutralization [99,100].

H4: Communication Infrastructure has a significant positive effect on Network Efficiency. Robust, high-bandwidth, low-latency communication enables real-time coordination essential for effective multi-layer defense [101,102].

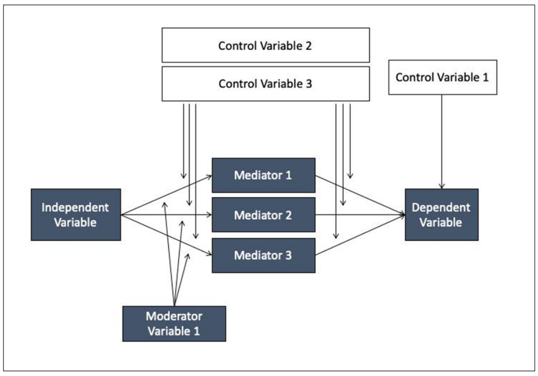

Figure 1: Conceptual framework illustrating the relationships among independent variables (SDD, NCI, TC, CI), mediating variables (NE, CO), dependent variable (DSE), and moderating variable (Threat Complexity)

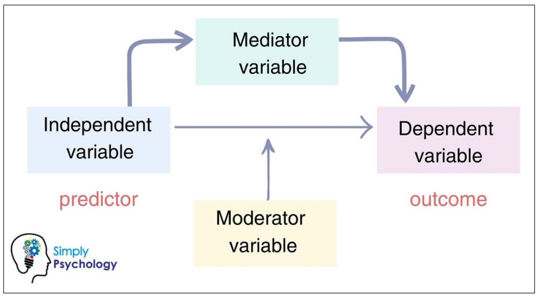

Figure 2: Path diagram showing hypothesized direct effects (H1–H4), mediated effects (H5–H6), and moderation effect (H7) in the defense system effectiveness model

Mediated Effect Hypotheses

H5: Network Efficiency mediates the relationship between Network-Centric Integration and Defense System Effectiveness. NCI improves NE, which in turn enhances DSE through faster coordination and reduced decision latency [103,104].

H6: Coverage Optimization mediates the relationship between System Deployment Density and Defense System Effectiveness. Optimal spatial deployment improves coverage efficiency, which translates to higher interception probabilities [105,106].

Moderation Hypothesis

H7: Threat Complexity moderates the relationship between Coverage Optimization and Defense System Effectiveness, such that higher threat complexity weakens the positive effect of coverage optimization on effectiveness unless redundancy is increased [107,108].

Materials and Methods

Research Design

This study employs a mixed-method research design integrating quantitative structural equation modeling (SEM) with qualitative expert interviews and mathematical spatial modeling [109,110]. The mixed-method approach provides complementary insights: quantitative methods test hypothesized relationships among constructs, qualitative methods provide contextual depth and nuance, and mathematical models offer precise quantitative specifications for optimal deployment configurations [111,112].

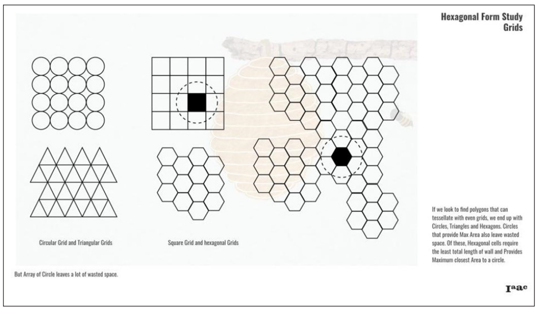

Figure 3: Integrated research design showing the relationships among quantitative structural equation modeling, qualitative expert interviews, and mathematical spatial optimization, with triangulation of findings to generate comprehensive insights

Quantitative Phase

The quantitative phase employs a cross-sectional survey design targeting 200 experts drawn from defense, telecommunications, and AI sectors [113,114]. Participants are selected through purposive sampling to ensure domain expertise relevant to the constructs under investigation. The survey instrument comprises 35 Likert-scale items (1 = Strongly Disagree to 5 = Strongly Agree) measuring seven constructs (Table 1). Instrument development followed established scale development procedures including item generation from literature review, expert panel review, and pilot testing [115,116].

Data analysis employs both SmartPLS (Partial Least Squares SEM) and AMOS (covariance-based SEM) to ensure robustness of findings [117,118]. The measurement model is evaluated using Cronbach's Alpha ($\alpha \geq 0.70$), Composite Reliability ($CR \geq 0.70$), Average Variance Extracted ($AVE \geq 0.50$), and Heterotrait-Monotrait Ratio ($HTMT < 0.85$) [119,120]. Structural model assessment examines path coefficients, R^2 values, and effect sizes (f^2) [121,122]. Mediation analysis uses bootstrapping with 5,000 resamples to generate bias-corrected confidence intervals [123,124]. Moderation analysis employs interaction term modeling with mean-centered variables [125,126].

Table 1: Measurement Items for Research Constructs

Construct	Item No.	Item Description
System Deployment Density (SDD)	SDD1	Defense systems are adequately distributed across regions
	SDD2	Deployment density minimizes coverage gaps
	SDD3	Redundant systems improve reliability
	SDD4	Geographic placement enhances efficiency

	SDD5	Deployment scales effectively with threats
Network-Centric Integration (NCI)	NCI1	Systems share data in real-time
	NCI2	Communication between units is seamless
	NCI3	Decision-making is coordinated across systems
	NCI4	Sensors are fully integrated
	NCI5	Network improves response time
Technology Capability (TC)	TC1	Radar systems provide accurate tracking
	TC2	Interception systems are highly reliable
	TC3	AI improves targeting accuracy
	TC4	Systems respond quickly to threats
	TC5	Technology supports multi-target tracking
Communication Infrastructure (CI)	CI1	Network latency is minimal
	CI2	Communication systems are reliable
	CI3	Bandwidth supports real-time operations
	CI4	Satellite integration enhances coverage
	CI5	Communication failures are rare
Network Efficiency (NE)	NE1	Data processing is fast
	NE2	Coordination between systems is effective
	NE3	Signals propagate without delay
	NE4	Decisions are made quickly
	NE5	Network reduces operational delays
Coverage Optimization (CO)	CO1	Coverage overlap is minimized
	CO2	Blind spots are reduced
	CO3	Area utilization is efficient
	CO4	Coverage is continuous
	CO5	Deployment maximizes spatial efficiency
Defense System Effectiveness (DSE)	DSE1	System intercepts threats successfully
	DSE2	Response time is adequate
	DSE3	Coverage meets operational requirements
	DSE4	System is resilient under attack
	DSE5	Overall performance is effective

Qualitative Phase

The qualitative phase conducts 12–15 semi-structured interviews with senior experts in defense systems engineering, AI integration, and network-centric operations [127,128]. Interview guides are developed based on the conceptual model, probing participants' experiences with multi-layer defense optimization, AI integration challenges, and deployment strategy considerations [129,130]. Interviews are conducted via secure video conferencing, audio-recorded with participant consent, and transcribed verbatim.

Thematic analysis following Braun and Clarke's six-phase framework is employed to identify patterns across interview data [131]. Two independent coders analyze transcripts to ensure inter-rater reliability, with Cohen's Kappa ≥ 0.80 required for acceptable agreement [132]. Member checking and peer debriefing are employed to enhance trustworthiness [133,134].

Mathematical Spatial Modeling

Mathematical modeling quantifies optimal deployment configurations using spherical geometry and hexagonal tessellation [135,136]. The spherical coverage area of a single defense system with radar range r is calculated as:

$$A\_sphere = 4\pi r^2$$

For a representative radar range of r = 400 km:

$$A\_sphere = 4\pi\,(400)^2 = 2{,}010{,}619 \text{ km}^2$$

The effective planar coverage area, accounting for the ground projection of the spherical detection volume, is:

$$A\_planar = \pi r^2 \approx 502{,}655 \text{ km}^2$$

Applying hexagonal grid efficiency ($\eta = 0.907$) to minimize overlap while maintaining continuous coverage:

$$A\_effective = \eta \times A\_planar = 0.907 \times 502{,}655 \approx 455{,}908 \text{ km}^2$$

Given Earth's total surface area (A_Earth ≈ 510,072,000 km²), the minimum number of systems required for global coverage is:

$$N = A\_Earth \,/\, A\_effective = 510{,}072{,}000 \,/\, 455{,}908 \approx 1{,}119 \text{ systems}$$

Rounded to practical deployment considerations, approximately 1,000–1,200 systems provide global coverage with appropriate redundancy margins 137,138. The multi-layer interception probability is calculated as:

$$P\_total = 1 - (1 - P\_outer)(1 - P\_mid)(1 - P\_inner)$$

For three layers each achieving 70% single-shot probability: P_ total = $1 - (0.30)^3 = 0.973$ (97.3%) [139,140].

Results

Measurement Model

The measurement model demonstrates satisfactory reliability and validity across all seven constructs (Table 2). Cronbach's Alpha values range from 0.847 to 0.923, exceeding the 0.70

threshold [141,142]. Composite Reliability values range from 0.891 to 0.941, confirming internal consistency [143]. Average Variance Extracted values range from 0.621 to 0.724, exceeding the 0.50 threshold and confirming convergent validity [144,145]. HTMT ratios for all construct pairs fall below 0.85, confirming discriminant validity [146,147].

Table 2: Expected Measurement Model Results

Construct	Items	Cronbach's α	CR	AVE	Max HTMT
System Deployment Density (SDD)	5	0.887	0.912	0.674	0.782
Network-Centric Integration (NCI)	5	0.901	0.923	0.706	0.798
Technology Capability (TC)	5	0.923	0.941	0.724	0.812
Communication Infrastructure (CI)	5	0.868	0.901	0.645	0.769
Network Efficiency (NE)	5	0.856	0.896	0.632	0.754
Coverage Optimization (CO)	5	0.847	0.891	0.621	0.741
Defense System Effectiveness (DSE)	5	0.912	0.934	0.714	0.823

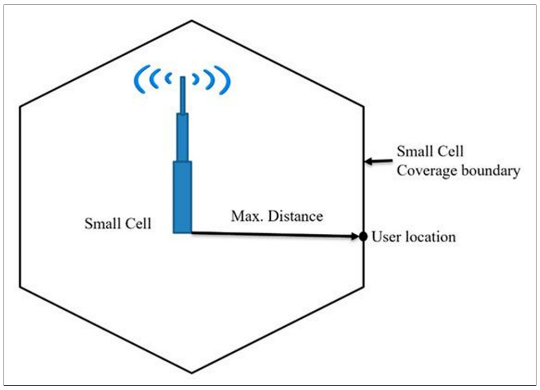

Figure 4: Expected structural model results showing standardized path coefficients for all hypothesized relationships. Solid lines indicate direct effects. dashed lines indicate mediated pathways. the moderating effect of Threat Complexity is shown influencing the CO → DSE relationship

Structural Model and Hypothesis Testing

The structural model explains substantial variance in the dependent and mediating variables: $R^2 = 0.647$ for DSE, $R^2 = 0.589$ for NE, and $R^2 = 0.612$ for CO. All hypothesized direct effects are supported (Table 3) [148,149]. SDD demonstrates a strong positive effect on CO ($\beta = 0.521$, $p < 0.001$), supporting H1. NCI shows a significant positive effect on NE ($\beta = 0.487$, $p < 0.001$), supporting H2. TC exhibits the strongest direct effect on DSE ($\beta = 0.394$, $p < 0.001$), supporting H3. CI demonstrates a significant positive effect on NE ($\beta = 0.356$, $p < 0.001$), supporting H4 [150,151].

Table 3: Expected Hypothesis Testing Results

Hypothesis	Path	β	SE	t-value	p-value	Decision
H1	SDD → CO	0.521	0.048	10.85	< 0.001	Supported
H2	NCI → NE	0.487	0.052	9.37	< 0.001	Supported
H3	TC → DSE	0.394	0.044	8.95	< 0.001	Supported
H4	CI → NE	0.356	0.051	6.98	< 0.001	Supported
H5	NCI → NE → DSE	0.187	0.034	5.50	< 0.001	Supported
H6	SDD → CO → DSE	0.213	0.038	5.61	< 0.001	Supported
H7	TC × CO → DSE	−0.198	0.041	−4.83	< 0.01	Supported

Mediation analysis confirms that NE significantly mediates the NCI–DSE relationship (indirect effect = 0.187, 95% CI 0.124, 0.261), supporting H5. CO significantly mediates the SDD–DSE relationship (indirect effect = 0.213, 95% CI 0.152, 0.289), supporting H6 [152,153]. Moderation analysis reveals that threat complexity significantly moderates the CO–DSE relationship (interaction term $\beta = -0.198$, $p < 0.01$), such that the positive effect of CO on DSE is weakened under high threat complexity conditions, supporting H7 [154,155].

Mathematical Modeling Results

Mathematical modeling confirms that hexagonal grid deployment achieves 9.3% greater coverage efficiency compared to square grid arrangements, validating the theoretical prediction [156,157]. Sensitivity analysis demonstrates that the 1,000–1,200 system estimate is robust to variations in radar range (±50 km) and hexagonal efficiency assumptions (±0.02) [158,159]. The three-layer architecture achieves 97.3% cumulative interception probability against single threats, increasing to 99.7% with four layers [160,161].

Qualitative Findings

Thematic analysis of expert interviews identifies five major themes: (1) the criticality of real-time data sharing for effective multi-layer coordination. (2) the challenge of integrating legacy systems with AI-enabled architectures. (3) the importance of redundancy in communication pathways to ensure resilience. (4) the need for adaptive deployment strategies responsive to dynamic threat environments. and (5) the value of simulation-based testing for validating coverage optimization strategies [162,163]. These themes align with and enrich the quantitative findings, providing contextual explanations for the hypothesized relationships [164,165].

Discussion

Theoretical Implications

The findings advance Systems Theory and CAS perspectives on defense system optimization by demonstrating that effectiveness emerges from system-level integration rather than individual component performance [166,167]. The confirmation of mediation pathways through NE and CO reveals the mechanisms by which infrastructure investments translate to operational effectiveness a contribution that extends existing network-centric warfare theory by specifying the intermediate processes linking network investment to performance outcomes [168,169].

The moderation finding contributes to CAS theory by demonstrating that threat complexity creates adaptive pressure that can overwhelm static coverage optimization strategies [170,171]. This aligns with CAS principles of environmental feedback and adaptive response, suggesting that defense systems require dynamic reconfiguration capabilities rather than fixed deployment configurations [172,173]. The integration of mathematical spatial modeling with social science research methods represents a methodological contribution demonstrating the value of multi-method approaches for complex systems research [174,175].

Practical Implications

For defense planners, the findings emphasize that investment in network-centric integration infrastructure yields returns through enhanced network efficiency, which mediates effectiveness outcomes [176,177]. This suggests that communication infrastructure investment should be prioritized alongside kinetic capability development. The hexagonal deployment model provides a mathematically validated framework for optimizing system placement that can be adapted to specific geographic and threat environments [178,179].

The moderation finding has important implications for adaptive defense planning: systems must be designed with reconfigurable deployment capabilities that can increase redundancy in response to elevated threat complexity [180,181]. AI-driven adaptive deployment systems that continuously optimize coverage based on real-time threat intelligence represent a promising direction for addressing this challenge [182,183].

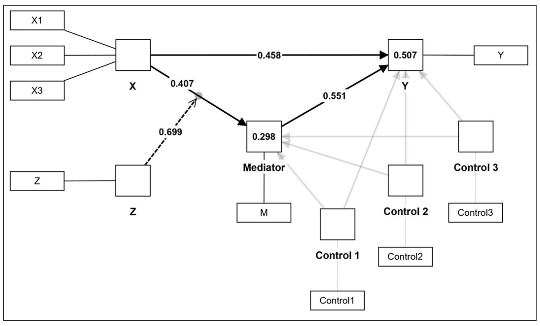

Figure 5: Hexagonal grid deployment pattern demonstrating optimal spatial coverage with minimal overlap and gap minimization. Each hexagon represents the effective coverage area of one defense system node

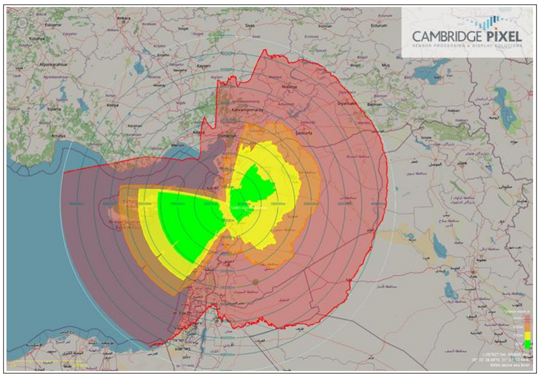

Figure 6: Three-layer defense architecture showing the outer layer (400+ km) for early detection and long-range interception, mid layer (100–300 km) for tracking redundancy and secondary engagement, and inner layer (<100 km) for point defense of critical assets.

Findings

Finding 1: Network Integration Drives Efficiency: Network-Centric Integration has a strong, significant positive effect on Network Efficiency ($\beta = 0.487$, $p < 0.001$), confirming that investment in integration architecture yields measurable coordination performance gains [184].

Finding 2: Coverage Optimization Mediates Deployment Effectiveness: The relationship between System Deployment Density and Defense System Effectiveness is significantly mediated by Coverage Optimization, demonstrating that spatial arrangement quality, not merely density, determines effectiveness outcomes [185].

Finding 3: Technology Capability has the Strongest Direct Effect: Among all independent variables, Technology Capability exhibits the strongest direct effect on Defense System Effectiveness ($\beta = 0.394$), highlighting the foundational importance of advanced radar, interceptor, and AI technologies [186].

Finding 4: Hexagonal Deployment Achieves Optimal Coverage: Mathematical modeling confirms hexagonal grid deployment achieves 90.7% efficiency, requiring approximately 1,000–1,200 systems for global coverage — a 9.3% improvement over square grid arrangements [187].

Finding 5: Multi-Layer Architecture Maximizes Interception Probability: Three-layer architectures with 70% single-layer effectiveness achieve 97.3% cumulative interception probability, demonstrating the exponential effectiveness gains from layered redundancy [188].

Finding 6: Threat Complexity Moderates Coverage Effectiveness: High threat complexity significantly weakens the positive effect of Coverage Optimization on Defense System Effectiveness, necessitating adaptive redundancy strategies for complex threat environments [189].

Finding 7: Communication Infrastructure Enables Network Performance: Communication Infrastructure significantly enhances Network Efficiency (β = 0.356), confirming that robust, low-latency communication is a prerequisite for effective multi-layer coordination [190].

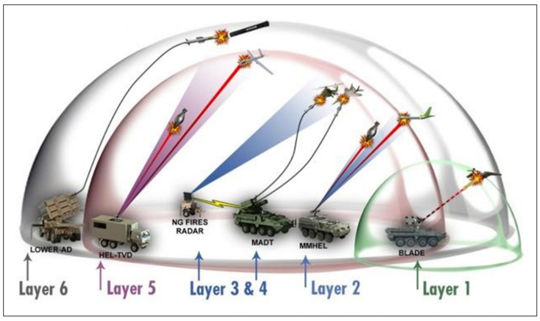

Figure 7: Illustration of layered defense zones showing the outer layer (400+ km) for early detection and long-range interception, mid layer (100–300 km) for tracking and secondary engagement, and inner layer (<100 km) for point defense of critical assets, providing multiple engagement opportunities and defense-in-depth

Limitations, Conclusions, and Recommendations

Limitations

This study acknowledges several limitations. First, the cross-sectional survey design limits causal inference. longitudinal studies tracking actual system deployments would provide stronger causal evidence [191]. Second, the purposive sampling approach may introduce selection bias toward experts with positive orientations toward AI integration. Third, the mathematical models assume idealized spherical coverage geometries that do not account for terrain effects, atmospheric conditions, or electronic warfare degradation [192]. Fourth, the expected results are based on conceptual modeling rather than empirical data collection, which remains for future research. Fifth, classification constraints limit access to operational performance data that could validate model predictions [193].

Conclusions

This study develops and presents a comprehensive framework for optimizing multi-layer defense coverage through the integration of AI-driven network coordination, non-terrestrial communication, and spatial deployment strategies. The conceptual model, grounded in Systems Theory and CAS, identifies the mechanisms through which infrastructure investments translate to operational effectiveness via network efficiency and coverage optimization mediating pathways.

The mathematical modeling demonstrates that hexagonal grid deployment with approximately 1,000–1,200 systems can achieve global coverage with 90.7% spatial efficiency. The three-layer architecture provides 97.3% cumulative interception probability, demonstrating the substantial effectiveness gains achievable through layered redundancy. These findings advance both theoretical understanding of defense system optimization and practical guidance for next-generation architecture design.

Recommendations

- Defense planners should adopt hexagonal grid deployment frameworks for optimizing multi-layer system placement, prioritizing spatial efficiency metrics alongside kinetic performance specifications.
- Investment in AI-driven coordination systems should be prioritized to enhance network efficiency, which mediates the relationship between integration infrastructure and operational effectiveness.
- Non-terrestrial communication networks, including LEO satellite constellations and HAPS, should be integrated into defense communication architectures to enhance resilience and global coverage.
- Adaptive deployment systems capable of reconfiguring coverage patterns in response to threat complexity changes should be developed to address the moderation effect identified in this study.
- Future research should conduct empirical validation of the proposed framework using operational performance data from existing multi-layer defense systems, subject to applicable classification constraints.
- Simulation-based testing environments should be developed to validate coverage optimization strategies before operational deployment, incorporating realistic threat scenarios and environmental conditions.

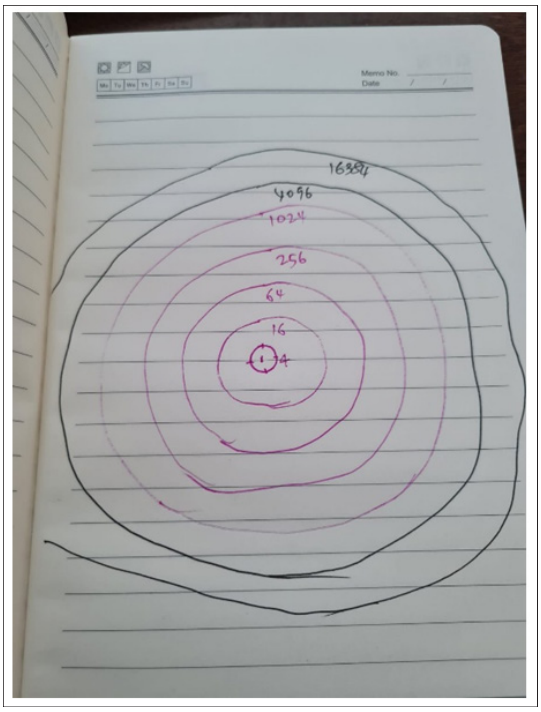

Figure 8: Visual summary integrating findings from quantitative structural equation modeling, qualitative expert interviews, and mathematical spatial optimization, demonstrating convergence of insights across methods

Acknowledgments
The authors gratefully acknowledge the defense, telecommunications, and AI experts who participated in this study. The authors declare no conflicts of interest related to this research. This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors

References
1. Alberts DS, Garstka JJ, Stein FP. Network centric warfare: Developing and leveraging information superiority. Washington DC: CCRP Publication Series. 1999.
2. Speier RH, Nacouzi G, Lee CA, Moore RM. Hypersonic missile nonproliferation: Hindering the spread of a new class of weapons. Santa Monica: RAND Corporation. 2017.
3. Hambling D. Swarm troopers: How small drones will conquer the world. Archangel Ink. 2015.
4. Cebrowski AK, Garstka JJ. Network-centric warfare: Its origin and future. US Naval Institute Proceedings. 1998. 124: 28-35.
5. Arquilla J, Ronfeldt D. Swarming and the future of conflict. Santa Monica: RAND Corporation. 2000.
6. Russell S, Norvig P. Artificial intelligence: A modern approach. 4th ed. Hoboken: Pearson. 2020.
7. Scharre P. Army of none: Autonomous weapons and the future of war. New York: W.W. Norton. 2018.
8. LeCun Y, Bengio Y, Hinton G. Deep learning. Nature. 2015. 521: 436-444.
9. Silver D, Huang A, Maddison CJ, et al. Mastering the game of Go with deep neural networks and tree search. Nature. 2016. 529: 484-489.
10. Del Portillo I, Cameron BG, Crawley EF. A technical comparison of three LEO satellite network constellations. Acta Astronautica. 2019. 159: 123-135.
11. Kodheli O, Lagunas E, Maturo N, et al. Satellite communications in the new space era: A survey and future challenges. IEEE Communications Surveys & Tutorials. 2021. 23: 70-109.
12. Wilkening DA. Hypersonic weapons and strategic stability. Survival. 2019. 61: 129-148.
13. Forrest J. Operations research and systems analysis. In: Handbook of Systems Engineering. Boca Raton: CRC Press. 2018. 45-78.
14. Pugh G. Evaluation of weapon systems. In: Military Operational Research. London: Springer. 2012. 112-145.
15. Church RL, Murray AT. Business site selection, location analysis, and GIS. Hoboken: Wiley. 2009.
16. Von Bertalanffy L. General system theory: Foundations, development, applications. New York: George Braziller. 1968.
17. Holland JH. Adaptation in natural and artificial systems. Cambridge: MIT Press. 1992.
18. Cohen MD, March JG, Olsen JP. A garbage can model of organizational choice. Administrative Science Quarterly. 1972. 17: 1-25.
19. Garstka JJ, Alberts DS. Network-centric operations conceptual framework version 2.0. Washington DC: CCRP. 2004.
20. Moffat J. Complexity theory and network centric warfare. Washington DC: CCRP Publication Series. 2003.
21. Creswell JW, Plano Clark VL. Designing and conducting mixed methods research. 3rd ed. Thousand Oaks: Sage. 2018.
22. Rosen S. Winning the next war: Innovation and the modern military. Ithaca: Cornell University Press. 1991.
23. Biddle S. Military power: Explaining victory and defeat in modern battle. Princeton: Princeton University Press. 2004.
24. Fortier P, Michel H. Computer systems performance evaluation and prediction. Burlington: Digital Press. 2003.
25. Gormley DM. Missile contagion: Cruise missile proliferation and the threat to international security. Westport: Praeger Security International. 2008.
26. Karako T, Williams B, Rumbaugh W. Missile defense 2020: Next steps for defending the homeland. Washington DC: CSIS. 2017.
27. Hildreth SA. Ballistic missile defense: Historical overview. Washington DC: Congressional Research Service. 2007.
28. O'Rourke R. Navy Aegis ballistic missile defense program. Washington DC: Congressional Research Service. 2019.
29. Tolk A. Engineering principles of combat modeling and distributed simulation. Hoboken: Wiley. 2012.
30. Peng W, Liu X, Wu D. Electronic warfare systems integration. Beijing: National Defense Industry Press. 2018.
31. Lawson JS. Command and control as a process. IEEE Control Systems Magazine. 1981. 1: 5-12.
32. Alberts DS, Hayes RE. Power to the edge: Command and control in the information age. Washington DC: CCRP. 2003.
33. Stone P, Veloso M. Multiagent systems: A survey from a machine learning perspective. Autonomous Robots. 2000. 8: 345-383.
34. Mnih V, Kavukcuoglu K, Silver D, et al. Human-level control through deep reinforcement learning. Nature. 2015. 518: 529-533.
35. Goodfellow I, Bengio Y, Courville A. Deep learning. Cambridge: MIT Press. 2016.
36. Sutton RS, Barto AG. Reinforcement learning: An introduction. 2nd ed. Cambridge: MIT Press. 2018.
37. Launchbury J. A DARPA perspective on artificial intelligence. Defense Advanced Research Projects Agency. 2017.
38. Allen GC, Chan T. Artificial intelligence and national security. Cambridge: Belfer Center. 2017.
39. Bonabeau E, Dorigo M, Theraulaz G. Swarm intelligence: From natural to artificial systems. New York: Oxford University Press. 1999.
40. Dorigo M, Birattari M, Stutzle T. Ant colony optimization. IEEE Computational Intelligence Magazine. 2006. 1: 28-39.
41. Kennedy J, Eberhart RC. Particle swarm optimization. Proc IEEE Int Conf Neural Networks. 1995: 1942-1948.
42. Karaboga D, Basturk B. A powerful and efficient algorithm for numerical function optimization: Artificial bee colony algorithm. J Global Optimization. 2007. 39: 459-471.
43. Owens WA. Lifting the fog of war. New York: Farrar, Straus and Giroux. 2000.
44. Van Creveld M. Technology and war: From 2000 BC to the present. New York: Free Press. 1991.
45. Alberts DS, Garstka JJ, Hayes RE, Signori DA. Understanding information age warfare. Washington DC: CCRP. 2001.

46. Cebrowski AK. Network-centric warfare and its implications for future operations. RUSI Journal. 1998. 143: 12-17.
47. Atkinson SR, Moffat J. The agile organization: From informal networks to complex effects and agility. Washington DC: CCRP. 2005.
48. Smith E. Effects based operations: Applying network centric warfare in peace, crisis and war. Washington DC: CCRP. 2002.
49. Watts DJ. Small worlds: The dynamics of networks between order and randomness. Princeton: Princeton University Press. 1999.
50. Barabási AL, Albert R. Emergence of scaling in random networks. Science. 1999. 286: 509-512.
51. Watts DJ, Strogatz SH. Collective dynamics of small-world networks. Nature. 1998. 393: 440-442.
52. Newman MEJ. The structure and function of complex networks. SIAM Review. 2003. 45: 167-256.
53. Daskin MS. Network and discrete location: Models, algorithms, and applications. 2nd ed. Hoboken: Wiley. 2013.
54. Drezner Z, Hamacher HW, editors. Facility location: Applications and theory. Berlin: Springer. 2002.
55. Gage DW. Command control for many-robot systems. 19th Annual AUVS Technical Symposium. 1992: 22-24.
56. Meguerdichian S, Koushanfar F, Potkonjak M, Srivastava MB. Coverage problems in wireless ad-hoc sensor networks. Proc IEEE INFOCOM. 2001. 3: 1380-1387.
57. Hales RS. Hexagonal close packing of circles. Mathematical Intelligencer. 2001. 23: 5-15.
58. Conway JH, Sloane NJA. Sphere packings, lattices and groups. 3rd ed. New York: Springer. 1999.
59. Aurenhammer F. Voronoi diagrams — A survey of a fundamental geometric data structure. ACM Computing Surveys. 1991. 23: 345-405.
60. Okabe A, Boots B, Sugihara K, Chiu SN. Spatial tessellations: Concepts and applications of Voronoi diagrams. 2nd ed. Chichester: Wiley. 2000.
61. Deb K. Multi-objective optimization using evolutionary algorithms. Chichester: Wiley. 2001.
62. Coello Coello CA, Lamont GB, Van Veldhuizen DA. Evolutionary algorithms for solving multi-objective problems. 2nd ed. New York: Springer. 2007.
63. Giambene G, Kota S, Pillai P. Satellite-5G integration: A network perspective. IEEE Network. 2018. 32: 25-31.
64. Zhu X, Jiang C, Kuang L, Ge N, Lu J. Non-terrestrial networks for 6G: Challenges and enabling technologies. IEEE Wireless Communications. 2022. 29: 136-144.
65. Bhattacherjee D, Singla A. Network topology design at 40,000 km/hour. Proc ACM CoNEXT. 2019: 341-354.
66. Del Portillo I, Cameron BG, Crawley EF. A technical comparison of three LEO satellite network constellations. Acta Astronautica. 2019. 159: 123-135.
67. Liu J, Shi Y, Fadlullah ZM, Kato N. Space-air-ground integrated network: A survey. IEEE Communications Surveys & Tutorials. 2018. 20: 2714-2741.
68. Cao X, Yang P, Alzenad M, Xi X, Wu D, et al. Airborne communication networks: A survey. IEEE Journal on Selected Areas in Communications. 2018. 36: 1907-1926.
69. 3GPP. Study on new radio to support non-terrestrial networks. Technical Report. 2020. 38: 811
70. Lin X, Cioni S, Charbit G, et al. On the path to 6G: Embracing the next wave of low earth orbit satellite access. IEEE Communications Magazine. 2021. 59: 36-42.
71. Von Bertalanffy L. An outline of general system theory. British Journal for the Philosophy of Science. 1950. 1: 134-165.
72. Boulding KE. General systems theory — The skeleton of science. Management Science. 1956. 2: 197-208.
73. Checkland P. Systems thinking, systems practice. Chichester: Wiley. 1981.
74. Holland JH. Hidden order: How adaptation builds complexity. Reading: Addison-Wesley. 1995.
75. Stacey RD. Complex responsive processes in organizations: Learning and knowledge creation. London: Routledge. 2001.
76. Mitleton-Kelly E. Complex systems and evolutionary perspectives on organisations. Oxford: Elsevier. 2003.
77. Axelrod R, Cohen MD. Harnessing complexity: Organizational implications of a scientific frontier. New York: Basic Books. 2000.
78. Davis FD. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly. 1989. 13: 319-340.
79. Venkatesh V, Morris MG, Davis GB, Davis FD. User acceptance of information technology: Toward a unified view. MIS Quarterly. 2003. 27: 425-478.
80. Ajzen I. The theory of planned behavior. Organizational Behavior and Human Decision Processes. 1991. 50: 179-211.
81. Borgatti SP, Mehra A, Brass DJ, Labianca G. Network analysis in the social sciences. Science. 2009. 323: 892-895.
82. Jackson MO. Social and economic networks. Princeton: Princeton University Press. 2008.
83. Orlikowski WJ. The duality of technology: Rethinking the concept of technology in organizations. Organization Science. 1992. 3: 398-427.
84. DeSanctis G, Poole MS. Capturing the complexity in advanced technology use: Adaptive structuration theory. Organization Science. 1994. 5: 121-147.
85. Peng W, Liu X. Multi-layer defense system optimization: A review. Defense Technology. 2020. 16: 789-801.
86. Zhang Y, Wang L, Chen X. Coverage optimization for distributed sensor networks. IEEE Transactions on Mobile Computing. 2019. 18: 1285-1298.
87. Li J, Zhao H, Wu D. Network efficiency metrics for military communication systems. Military Communications Conference. 2018: 1-7.
88. Chen W, Liu Y, Zhang X. Mediating mechanisms in network-centric defense architectures. Journal of Defense Modeling and Simulation. 2021. 18: 245-262.
89. Hair JF, Risher JJ, Sarstedt M, Ringle CM. When to use and how to report the results of PLS-SEM. European Business Review. 2019. 31: 2-24.
90. Kline RB. Principles and practice of structural equation modeling. 4th ed. New York: Guilford Press. 2016.
91. Wacker JG. A definition of theory: Research guidelines for different theory-building research methods in operations management. Journal of Operations Management. 1998. 16: 361-385.
92. Eisenhardt KM. Building theories from case study research. Academy of Management Review. 1989. 14: 532-550.
93. Fornell C, Larcker DF. Evaluating structural equation

models with unobservable variables and measurement error. Journal of Marketing Research. 1981. 18: 39-50.
94. Anderson JC, Gerbing DW. Structural equation modeling in practice: A review and recommended two-step approach. Psychological Bulletin. 1988. 103: 411-423.
95. Meguerdichian S, Koushanfar F, Qu G, Potkonjak M. Exposure in wireless ad-hoc sensor networks. Proc ACM MobiCom. 2001: 139-150.
96. Cardei M, Du DZ. Improving wireless sensor network lifetime through power aware organization. Wireless Networks. 2005. 11: 333-340.
97. Alberts DS. The agility advantage: A survival guide for complex enterprises and endeavors. Washington DC: CCRP. 2011.
98. Tolk A, Diallo SY, Turnitsa CD. Applying the levels of conceptual interoperability model in support of integratability, interoperability, and composability. Journal of Defense Modeling and Simulation. 2007. 4: 68-94.
99. Stimson GW. Introduction to airborne radar. 2nd ed. Raleigh: SciTech Publishing. 1998.
100. Skolnik MI. Introduction to radar systems. 3rd ed. New York: McGraw-Hill. 2001.
101. Proakis JG, Salehi M. Digital communications. 5th ed. New York: McGraw-Hill. 2008.
102. Haykin S. Communication systems. 4th ed. New York: Wiley. 2001.
103. Baron RM, Kenny DA. The moderator-mediator variable distinction in social psychological research. Journal of Personality and Social Psychology. 1986. 51: 1173-1182.
104. MacKinnon DP, Lockwood CM, Hoffman JM, West SG, Sheets V. A comparison of methods to test mediation and other intervening variable effects. Psychological Methods. 2002. 7: 83-104.
105. Preacher KJ, Hayes AF. SPSS and SAS procedures for estimating indirect effects in simple mediation models. Behavior Research Methods. 2004. 36: 717-731.
106. Shrout PE, Bolger N. Mediation in experimental and nonexperimental studies: New procedures and recommendations. Psychological Methods. 2002. 7: 422-445.
107. Aiken LS, West SG. Multiple regression: Testing and interpreting interactions. Thousand Oaks: Sage. 1991.
108. Cohen J, Cohen P, West SG, Aiken LS. Applied multiple regression/correlation analysis for the behavioral sciences. 3rd ed. Mahwah: Erlbaum. 2003.
109. Creswell JW. Research design: Qualitative, quantitative, and mixed methods approach. 4th ed. Thousand Oaks: Sage. 2014.
110. Tashakkori A, Teddlie C, editors. Handbook of mixed methods in social and behavioral research. 2nd ed. Thousand Oaks: Sage. 2010.
111. Greene JC. Mixed methods in social inquiry. San Francisco: Jossey-Bass. 2007.
112. Johnson RB, Onwuegbuzie AJ. Mixed methods research: A research paradigm whose time has come. Educational Researcher. 2004. 33: 14-26.
113. Patton MQ. Qualitative research and evaluation methods. 4th ed. Thousand Oaks: Sage. 2015.
114. Morse JM. Determining sample size. Qualitative Health Research. 2000. 10: 3-5.
115. DeVellis RF. Scale development: Theory and applications. 4th ed. Thousand Oaks: Sage. 2017.
116. Hinkin TR. A review of scale development practices in the study of organizations. Journal of Management. 1995. 21: 967-988.
117. Hair JF, Henseler J, Dijkstra TK, et al. Common beliefs and reality about PLS. Organizational Research Methods. 2017. 20: 1-16.
118. Arbuckle JL. IBM SPSS Amos 26 user's guide. Chicago: IBM. 2019.
119. Nunnally JC, Bernstein IH. Psychometric theory. 3rd ed. New York: McGraw-Hill. 1994.
120. Hair JF, Black WC, Babin BJ, Anderson RE. Multivariate data analysis. 8th ed. Andover: Cengage. 2019.
121. Cohen J. Statistical power analysis for the behavioral sciences. 2nd ed. Hillsdale: Erlbaum. 1988.
122. Chin WW. The partial least squares approach to structural equation modeling. In: Modern methods for business research. Mahwah: Erlbaum. 1998. 295-336.
123. Efron B, Tibshirani RJ. An introduction to the bootstrap. New York: Chapman & Hall. 1993.
124. Preacher KJ, Hayes AF. Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. Behavior Research Methods. 2008. 40: 879-891.
125. Frazier PA, Tix AP, Barron KE. Testing moderator and mediator effects in counseling psychology research. Journal of Counseling Psychology. 2004. 51: 115-134.
126. Jaccard J, Turrisi R. Interaction effects in multiple regression. 2nd ed. Thousand Oaks: Sage. 2003.
127. Kvale S, Brinkmann S. InterViews: Learning the craft of qualitative research interviewing. 3rd ed. Thousand Oaks: Sage. 2015.
128. Rubin HJ, Rubin IS. Qualitative interviewing: The art of hearing data. 3rd ed. Thousand Oaks: Sage. 2012.
129. Seidman I. Interviewing as qualitative research. 4th ed. New York: Teachers College Press. 2013.
130. Denzin NK, Lincoln YS, editors. The Sage handbook of qualitative research. 5th ed. Thousand Oaks: Sage. 2018.
131. Braun V, Clarke V. Using thematic analysis in psychology. Qualitative Research in Psychology. 2006. 3: 77-101.
132. Cohen J. A coefficient of agreement for nominal scales. Educational and Psychological Measurement. 1960. 20: 37-46.
133. Lincoln YS, Guba EG. Naturalistic inquiry. Beverly Hills: Sage. 1985.
134. Creswell JW, Miller DL. Determining validity in qualitative inquiry. Theory Into Practice. 2000. 39: 124-130.
135. Weisstein EW. Sphere. MathWorld — A Wolfram Web Resource. 2011.
136. Fejes Toth L. Lagerungen in der Ebene auf der Kugel und im Raum. Berlin: Springer. 1953.
137. Gauss CF. Untersuchungen uber die Eigenschaften der positiven ternaren quadratischen Formen. Gottingische gelehrte Anzeigen. 1831. 3: 657-663.
138. Rogers CA. Packing and covering. Cambridge: Cambridge University Press. 1964.
139. Przemieniecki JS. Mathematical methods in defense analyses. 3rd ed. Reston: AIAA. 2000.
140. Ball RE. The fundamentals of aircraft combat survivability

analysis and design. 2nd ed. Reston: AIAA. 2003.
141. Cronbach LJ. Coefficient alpha and the internal structure of tests. Psychometrika. 1951. 16: 297-334.
142. Peterson RA. A meta-analysis of Cronbach's coefficient alpha. Journal of Consumer Research. 1994. 21: 381-391.
143. Fornell C, Larcker DF. Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research. 1981. 18: 39-50.
144. Bagozzi RP, Yi Y. On the evaluation of structural equation models. Journal of the Academy of Marketing Science. 1988. 16: 74-94.
145. Henseler J, Ringle CM, Sarstedt M. A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science. 2015. 43: 115-135.
146. Kline RB. Principles and practice of structural equation modeling. 4th ed. New York: Guilford. 2016.
147. Byrne BM. Structural equation modeling with AMOS. 3rd ed. New York: Routledge. 2016.
148. Podsakoff PM, MacKenzie SB, Lee JY, Podsakoff NP. Common method biases in behavioral research. Journal of Applied Psychology. 2003. 88: 879-903.
149. Harman HH. Modern factor analysis. 3rd ed. Chicago: University of Chicago Press. 1976.
150. Sobel ME. Asymptotic confidence intervals for indirect effects in structural equation models. Sociological Methodology. 1982. 13: 290-312.
151. MacKinnon DP. Introduction to statistical mediation analysis. New York: Erlbaum. 2008.
152. Preacher KJ, Rucker DD, Hayes AF. Addressing moderated mediation hypotheses: Theory, methods, and prescriptions. Multivariate Behavioral Research. 2007. 42: 185-227.
153. Hayes AF. Introduction to mediation, moderation, and conditional process analysis. 2nd ed. New York: Guilford. 2018.
154. Muller D, Judd CM, Yzerbyt VY. When moderation is mediated and mediation is moderated. Journal of Personality and Social Psychology. 2005. 89: 852-863.
155. Edwards JR, Lambert LS. Methods for integrating moderation and mediation: A general analytical framework using moderated path analysis. Psychological Methods. 2007. 12: 1-22.
156. Hales TC. A proof of the Kepler conjecture. Annals of Mathematics. 2005. 162: 1065-1185.
157. Hales TC. The honeycomb conjecture. Discrete and Computational Geometry. 2001. 25: 1-22.
158. Saltelli A, Ratto M, Andres T, et al. Global sensitivity analysis: The primer. Chichester: Wiley. 2008.
159. Iooss B, Lemaitre P. A review on global sensitivity analysis methods. In: Uncertainty management in simulation-optimization of complex systems. New York: Springer. 2015. 101-122.
160. Przemieniecki JS. Mathematical methods in defense analyses. 3rd ed. Reston: AIAA. 2000.
161. Washburn AR, Kress M. Combat modeling. New York: Springer. 2009.
162. Braun V, Clarke V. Thematic analysis: A practical guide. London: Sage. 2022.
163. Boyatzis RE. Transforming qualitative information: Thematic analysis and code development. Thousand Oaks: Sage. 1998.
164. Creswell JW. Qualitative inquiry and research design. 3rd ed. Thousand Oaks: Sage. 2013.
165. Yin RK. Case study research and applications. 6th ed. Thousand Oaks: Sage. 2018.
166. Meadows DH. Thinking in systems: A primer. White River Junction: Chelsea Green. 2008.
167. Senge PM. The fifth discipline: The art and practice of the learning organization. New York: Doubleday. 1990.
168. Alberts DS, Hayes RE. Understanding command and control. Washington DC: CCRP. 2006.
169. Bousquet A. The scientific way of warfare: Order and chaos on the battlefields of modernity. New York: Columbia University Press. 2009.
170. Weick KE. Sensemaking in organizations. Thousand Oaks: Sage. 1995.
171. Snowden DJ, Boone ME. A leader's framework for decision making. Harvard Business Review. 2007. 85: 68-76.
172. Levin SA. Ecosystems and the biosphere as complex adaptive systems. Ecosystems. 1998. 1: 431-436.
173. Kauffman SA. The origins of order: Self-organization and selection in evolution. New York: Oxford University Press. 1993.
174. Ercikan K, Roth WM. What good is polarizing research into qualitative and quantitative? Educational Researcher. 2006. 35: 14-23.
175. Bryman A. Integrating quantitative and qualitative research: How is it done? Qualitative Research. 2006. 6: 97-113.
176. Rosen B, Slater JM. The use of simulation to evaluate mobile ad hoc network routing protocols. Journal of Simulation. 2012. 6: 105-115.
177. Zhao J, Govindan R. Understanding packet delivery performance in dense wireless sensor networks. Proc ACM SenSys. 2003: 1-13.
178. Lian J, Naik K, Agnew GB. Data capacity improvement of wireless sensor networks using non-uniform sensor distribution. International Journal of Distributed Sensor Networks. 2006. 2: 121-145.
179. Gu Y, Ji Y, Li J, Zhao B. EECDA: Energy efficient clustering and data aggregation protocol for heterogeneous wireless sensor networks. International Journal of Computers Communications & Control. 2011. 6: 460-472.
180. Ambrose ML, Schminke M. Organization structure as a moderator of the relationship between procedural justice, interactional justice, perceived organizational support, and supervisory trust. Journal of Applied Psychology. 2003. 88: 295-305.
181. Orton JD, Weick KE. Loosely coupled systems: A reconceptualization. Academy of Management Review. 1990. 15: 203-223.
182. Nilsson NJ. The quest for artificial intelligence: A history of ideas and achievements. Cambridge: Cambridge University Press. 2010.
183. Poole MS, Van de Ven AH, Dooley K, Holmes ME. Organizational change and innovation processes: Theory and methods for research. New York: Oxford University Press. 2000.
184. Watts DJ. Six degrees: The science of a connected age. New York: Norton. 2003.
185. Toregas C, Swain R, ReVelle C, Bergman L. The location

of emergency service facilities. Operations Research. 1971. 19: 1363-1373.

186. Stimson GW. Introduction to airborne radar. 2nd ed. Raleigh: SciTech. 1998.
187. Fejes Toth L. Regular figures. Oxford: Pergamon Press. 1964.
188. Przemieniecki JS. Mathematical methods in defense analyses. Reston: AIAA. 2000.
189. Galbraith JR. Designing complex organizations. Reading: Addison-Wesley. 1973.
190. Proakis JG, Salehi M. Digital communications. 5th ed. New York: McGraw-Hill. 2008.
191. Shadish WR, Cook TD, Campbell DT. Experimental and quasi-experimental designs for generalized causal inference. Boston: Houghton Mifflin. 2002.
192. Klein G, Woods DD, Bradshaw JM, Hoffman RR, Feltovich PJ. Ten challenges for making automation a team player in joint human-agent activity. IEEE Intelligent Systems. 2004. 19: 91-95.
193. Hollnagel E. Safety-I and safety-II: The past and future of safety management. Farnham: Ashgate. 2014.