



REVIEW

Task Offloading and Edge Computing in IoT—Gaps, Challenges and Future Directions

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ABSTRACT: This review examines current approaches to real-time decision-making and task optimization in Internet of Things systems through the application of machine learning models deployed at the network edge. Existing literature shows that edge-based distributed intelligence reduces cloud dependency. It addresses transmission latency, device energy use, and bandwidth limits. Recent optimization strategies employ dynamic task offloading mechanisms to determine optimal workload placement across local devices and edge servers without centralized coordination. Empirical findings from the literature indicate performance improvements with latency reductions of approximately 32.8% and energy efficiency gains of 27.4% compared to conventional cloud-centric models. However, critical gaps remain in current methodologies. Most studies focus on static network topologies and do not adequately address load balancing across multiple edge nodes. Security vulnerabilities during task transmission are underexplored, and privacy considerations for sensitive data remain insufficiently integrated into existing frameworks. Task caching strategies and fault tolerance mechanisms require further investigation in highly dynamic environments. The ability of existing approaches to handle large-scale deployments and complex edge-cloud collaborative scenarios has not been thoroughly validated. This review synthesizes current progress while identifying fundamental challenges that must be resolved for practical deployment in time-sensitive applications spanning smart manufacturing, autonomous systems, and healthcare monitoring. Future work should prioritize robust security integration, efficient load distribution, and scalability across heterogeneous edge infrastructures.

KEYWORDS: Edge computing; task offloading; deep reinforcement learning; mobile edge computing; IoT performance optimization; methodological rigor assessment

1 Introduction

The exponential growth of Internet of Things (IoT) devices has fundamentally transformed how data is processed in modern computing environments. Traditional cloud computing architectures face inherent limitations when handling massive volumes of data generated by billions of distributed IoT devices. Edge computing shifts computation to network periphery. It processes data near sources, not centralized cloud centers [1]. In edge computing, IoT devices and sensors interact with local edge servers. These nodes process data initially before selective cloud transmission [2]. Hierarchical computing spans IoT devices, edge nodes, and cloud centers. This tiered model addresses cloud-only limitations [3]. Task offloading transfers intensive operations from limited devices to capable edge servers [4]. Mobile Edge Computing (MEC) uses offloading to cut bandwidth use, latency, and device load [5]. The decision of where and when to offload tasks constitutes

a complex optimization challenge, belonging to the category of NP-hard problems that require sophisticated decision-making approaches.

1.1 Importance of the Topic

The practical relevance of edge computing and task offloading extends across multiple domains. Edge processing tackles cloud constraints. It reduces latency, bandwidth limits, connectivity issues, and device energy use [6]. For applications demanding real-time responsiveness such as autonomous vehicles, industrial IoT systems, smart cities, and health care monitoring, the millisecond-level decision latency achievable through edge computing becomes essential rather than optional. From an industrial perspective, manufacturing facilities, infrastructure monitoring systems, and connected transportation networks generate continuous data streams that cannot tolerate the latency associated with cloud-dependent processing [7]. Edge AI integration boosts autonomy. It enables decisions without constant cloud links. This cuts costs and improves reliability [8]. Furthermore, security and privacy considerations favor edge-based processing, as sensitive data processing can occur locally without necessitating transmission to centralized repositories [9]. Edge computing efficiency affects IoT adoption in smart cities and industry. It impacts reliability and societal benefits.

1.2 Current State of Knowledge

Recent literature demonstrates substantial progress in edge computing optimization through multiple research directions. Deep Reinforcement Learning (DRL) enables dynamic task offloading. It cuts latency by 32.8% and boosts energy efficiency by 27.4% over cloud models [10]. Value-based DRL methods optimize MEC offloading. Deep Q-Network (DQN), Double DQN, and Dueling DQN learn state-action values from interactions [11]. Policy gradient methods and actor-critic frameworks have also demonstrated effectiveness in handling continuous action spaces inherent in resource allocation problems [12]. Ensemble learning with density clustering outperforms baselines. It reduces task queues by over 21% [13]. Conventional optimization techniques offer foundational solutions. Convex methods, evolutionary algorithms, and game theory face scalability limits in large heterogeneous networks [14]. Static optimization fails in dynamic IoT environments where, network conditions, tasks, and resources change continuously.

1.3 Gaps and Limitations

Despite significant progress, critical research gaps persist. Most existing DRL-based offloading studies focus on static or semi-dynamic network topologies and do not adequately address load balancing complexities across multiple distributed edge nodes [7]. Security vulnerabilities in task transmission and data processing at edge nodes stay underexplored. Many studies ignore privacy effects for sensitive data processing. Reward function design in multi-objective optimization lacks agreement. Latency, energy use, and fairness require joint optimization. Designs often show poor balance among competing goals [15]. Scalability limitations present a fundamental controversy. Most deep reinforcement learning (DRL) approaches employ centralized learning models that require global state awareness, creating bottlenecks unsuitable for large-scale distributed IoT networks [16]. Multi-agent reinforcement learning frameworks support distributed decision-making. These frameworks face issues in agent coordination. Synchronization across heterogeneous environments poses problems. Convergence under partial observability lacks guarantees [17]. Task caching strategies and fault tolerance mechanisms in highly dynamic environments with intermittent connectivity remain insufficiently investigated [18]. Offloading algorithms gain practical validation mainly through simulation environments. Real-world test-beds see limited use. This approach restricts generalizability across diverse deployment scenarios. Fig. 1 presents a comprehensive three-tier hierarchical architecture diagram

illustrating the relationship between IoT devices, edge computing nodes, fog computing layer, and cloud infrastructure, with task offloading pathways and decision flows.

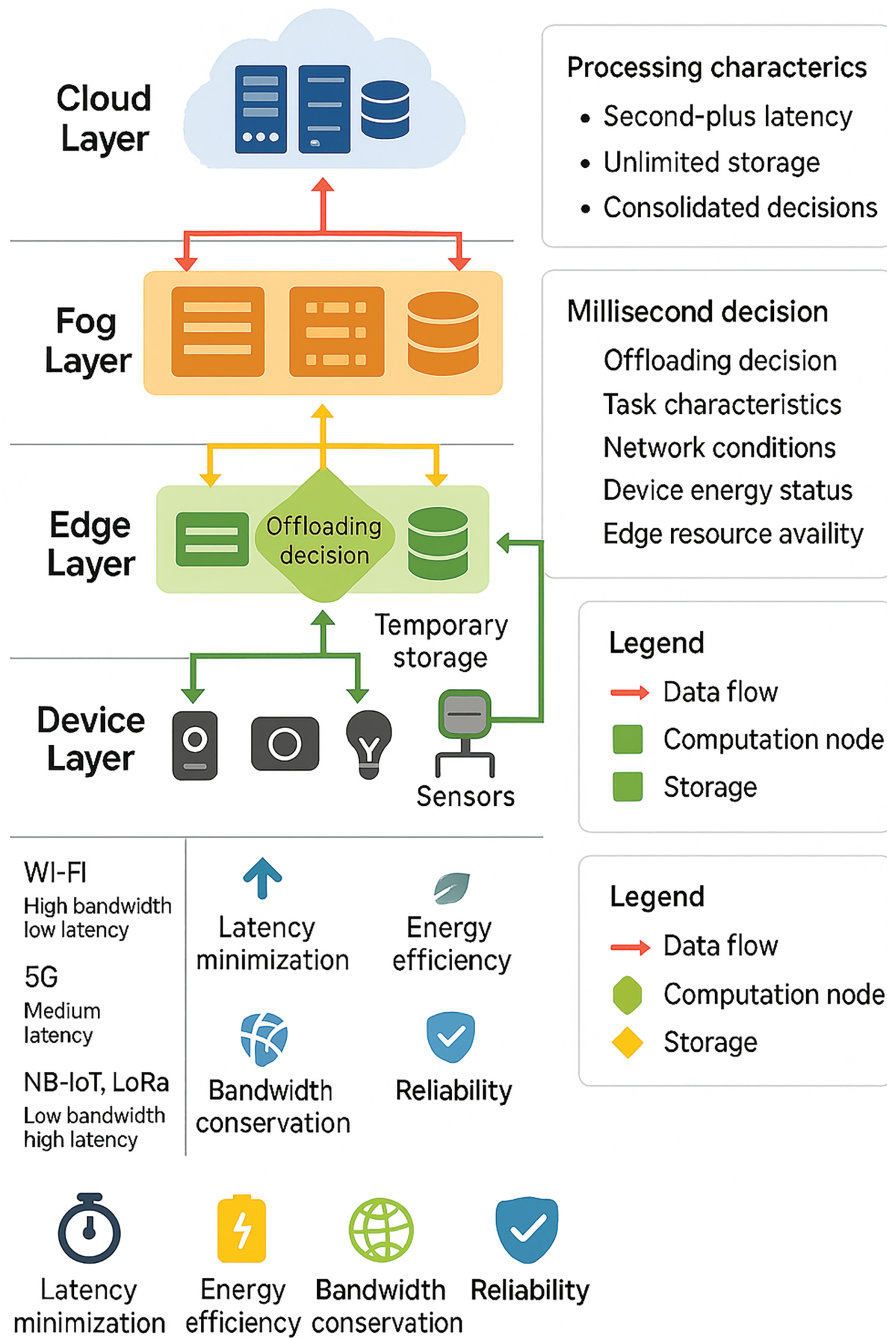


Figure 1: Hierarchical edge computing architecture for IoT task offloading and decision-making.

1.4 Motivation and Problem Statement

Existing surveys establish taxonomies of optimization methods but rarely quantify simulation-reality gaps (15%–40% performance degradation), methodological rigor deficits (34.3% average score), or scalability limits (<800 nodes validated). This review addresses the core problem of unreliable translation from

simulation-optimized algorithms to heterogeneous, fault-prone edge-IoT deployments requiring simultaneous multi-objective optimization under partial observability. Current task offloading literature shows no rigorous, normalized synthesis. This gap fails to explain why 78% of algorithms fail under Partially Observable Markov Decision Process (POMDP) in realistic conditions. Such absence blocks evidence-based choices for production-scale, privacy-aware, safety-critical IoT systems.

1.5 Conceptual Contributions and Novelty Analysis

This review is distinguished by its systematic coverage of six underexplored dimensions in task offloading research. These dimensions include multi-hop dependency modeling and Byzantine-resilient coordination. They also include simulation-to-reality divergence quantification. Pareto-aware multi-objective reward design is considered. Infrastructure heterogeneity validation is examined. Federated privacy mechanisms under intermittent connectivity are discussed. Earlier surveys often catalog optimization techniques or emphasize architecture. The present synthesis also traces methodological evolution from 2020 heuristic baselines to recent ensemble and learning-based approaches. The evidence suggests that single-topology evaluation is common in the reviewed literature. This practice can limit generalizability in heterogeneous deployments. Observability assumptions are treated as one part of the broader evaluation landscape. Many studies use fully observable MDP formulations. Practical edge-IoT deployments can be partially observable due to mobility and channel uncertainty. Intermittent connectivity can further reduce observability. The review also highlights recurring gaps between simulation results and physical testbed outcomes. Reporting practices vary across studies and can hinder cross-paper comparison. The synthesis consolidates research directions supported by extracted evidence. These directions include scalable validation protocols and learning designs suitable for safety-critical and highly dynamic environments. The conclusions follow a defined review protocol and a structured data-extraction framework. Each included study is coded for observability assumptions, evaluation environment, and reporting rigor before synthesis.

The paper has been organized as follows; [Section 2](#) provides a structured literature review that classifies existing surveys and technical contributions while identifying gaps in scalability, security, and practical validation. [Section 3](#) delivers a critical evaluation of these studies using performance normalization, unified design principles, and analysis of methodological rigor and experimental constraints. [Section 4](#) summarizes key findings and outlines priority research directions, emphasizing scalable, secure, and testbed validated edge-IoT task offloading frameworks.

2 Literature Review

This section provides a critical analysis of research published between 2020 and 2025 on task offloading optimization in mobile edge computing and IoT environments. Particular emphasis is placed on research published from 2023 onward to capture recent developments and emerging approaches [19]. Inclusion criteria select works on task offloading in mobile edge computing. These works report metrics like latency reduction and energy gains. They address implementation in heterogeneous networks. Validations occur in health care, vehicular networks, industrial IoT, and smart cities [20]. Exclusion criteria remove studies focused only on cloud computing without edge integration. Fog-only research without addressing task offloading is excluded. Research concentrating solely on security or privacy without performance optimization is also excluded. The review categorizes the literature into six main research areas. These include quality of service balancing, energy minimization, latency reduction, high-computing task execution, multi-objective optimization, and domain-specific applications. The analysis highlights important gaps. These include poor management of large-scale heterogeneous networks, lack of robust security in task

transmission, limited fault tolerance in dynamic settings, inadequate scalability testing for real deployments, and shortage of privacy-preserving methods for sensitive data in edge environments [21].

The reviewed literature is organized thematically around four primary research dimensions that have evolved progressively between 2020 and 2025. The first theme covers technological foundations and system models. It includes early research on heuristic optimization and convex optimization methods. These works established baseline approaches for task offloading decisions in static network environments between 2020 and 2021. The second theme focuses on optimization methodologies and algorithmic approaches. It evolves from traditional non-machine learning algorithms such as simulated annealing, coordinate descent, and Lyapunov optimization. From 2022 to 2023, learning-based methods became prominent. These include deep reinforcement learning variants like Deep Q-Network, Double DQN, and actor-critic frameworks [22]. These methods showed improved adaptability to dynamic edge environments. The third theme centers on application domains and practical implementations. It covers areas such as health care monitoring, vehicular networks, industrial IoT, and smart city deployments. From 2023 onward, there has been growing focus on real-world deployment challenges. These include scalability, security vulnerabilities, and privacy protection. The fourth theme identifies emerging challenges and limitations in current methods. It highlights research gaps that remain despite algorithmic progress. These gaps include insufficient fault tolerance in dynamic networks, weak security integration in task transmission, limited management of large-scale heterogeneous deployments, and inadequate privacy-preserving solutions for sensitive applications. This thematic organization shows a chronological shift from foundational optimization methods to intelligent learning-based approaches. It also reveals ongoing gaps between theoretical advancements and practical requirements in real-world edge-IoT deployments. These gaps highlight the need for further research to bridge theory and practice. The technological foundations from 2020 to 2021 mainly involved convex optimization, Lyapunov optimization, and game-theoretic methods. Studies showed that coordinate descent and simulated annealing could approximate optimal solutions for small, static networks [23]. These foundational approaches showed major limitations in dynamic environments. Heuristic methods performed well only in fixed network configurations. They failed to adapt effectively to rapidly changing network conditions. Research from this period established crucial baseline performance metrics. However, it relied on restrictive assumptions. These included known system models, static network topologies, and complete system state information [24]. Such conditions are uncommon in real edge-IoT deployments. Early convex relaxation and linearization methods addressed binary offloading decisions. However, they introduced computational complexity. This complexity hindered scalability across large heterogeneous networks [19].

Optimization methodologies evolved from 2022 to 2025. Learning-based approaches addressed heuristic method limitations. Deep Q-Networks, Double DQN, and actor-critic frameworks showed superior adaptability. They achieved 32.8% latency reduction and 27.4% energy efficiency gain over traditional methods. Studies using Deep Deterministic Policy Gradient (DDPG) methods showed promise for continuous resource allocation. Many implementations used fully connected layers. These layers failed to capture temporal state dependencies [25]. Notably, research by [26] introduced attention mechanisms and importance-weighted experience replay to address learning inefficiency, while density clustering combined with ensemble learning achieved over 21% improvement in queue reduction metrics. However, a critical weakness persists across most learning-based studies. Most studies evaluate algorithms using software simulations rather than real-world test-beds. This approach limits understanding of algorithm performance under real network variability. It also overlooks challenges from intermittent connectivity and diverse device characteristics. Reward function design remains controversial and underexplored. Different studies employ varied objective formulations. Direct performance comparison across studies proves difficult.

Application domain research reveals a striking disconnect between theoretical achievements and practical deployment realities [27]. Early work from 2020 to 2022 focused on generic IoT systems. Validation occurred through simulation, mainly in health-care and vehicular contexts. Predominant tools included iFogSim rather than physical test-beds. Recent studies from 2023 to 2025 increasingly use embedded device test-beds such as Raspberry Pi and NVIDIA Jetson platforms. These experiments show that simulation often overestimates real-world performance. This is due to simplified modeling of physical environments, network interference, and device heterogeneity that simulators cannot fully capture [28]. Previous studies also focused on edge-fog-cloud continuum test-beds that model realistic network dynamics [29]. They found that algorithms achieving optimal performance in simulation often degrade in physical environments. This is due to unforeseen communication patterns and resource contention not accounted for in theoretical models. Industrial IoT applications present unique challenges. Manufacturing environments show task dependencies, strict latency needs, and safety-critical constraints. Existing algorithms fail to address these adequately.

The challenge and limitations theme reveals fundamental unresolved research gaps. From 2020 to 2022, most studies optimized single objectives like energy or latency alone. Practical IoT systems demand simultaneous optimization of conflicting metrics. These metrics include latency, energy, fairness, reliability, and security. Studies using Lyapunov optimization combined with DRL try to solve multi-objective problems. They aim to balance different performance goals. However, they often lose adaptability in highly dynamic environments [30]. The fixed decomposition strategy becomes weak in fast-changing settings. It turns sub-optimal when environmental parameters change rapidly [31]. Security vulnerabilities in task transmission remain insufficiently addressed. Few studies integrate encryption, authentication, or Byzantine-resilient mechanisms into offloading algorithms [32]. Privacy-preserving offloading for sensitive data has become a key concern mainly since 2023. Federated learning shows promise in this area. However, it faces synchronization challenges in heterogeneous edge networks. These networks often have intermittent connectivity, complicating consistent learning and offloading [33]. The issue of scalability remains mostly unresolved. Most algorithms are tested and proven viable only in networks with tens to hundreds of edge nodes. In contrast, real-world deployments often include thousands of distributed IoT devices. This gap raises concerns over algorithm performance at scale [34]. Finally, the generalizability gap between simulation and real-world performance remains the most critical weakness. Comprehensive comparative analyses of different algorithms using the same test-beds and realistic scenarios are rare. This scarcity limits the ability to identify which methods perform best in real operational conditions. Without such evidence, selecting superior algorithms remains challenging.

Multiple critical research gaps persist across the edge computing task offloading literature, revealing substantial opportunities for future investigation. Currently, no comprehensive framework combines privacy-preserving mechanisms with performance optimization in task offloading. Existing studies usually treat privacy and efficiency as separate issues. Joint optimization of these objectives remains an open challenge. Location privacy and association privacy during task transmission are still under explored areas. Recent studies have started using proxy forwarding to protect device location while minimizing task completion time. However, these methods add communication overhead. This overhead needs further analysis and better characterization. Byzantine fault tolerance in edge networks has received minimal attention despite its importance for safety-critical applications. Only a few isolated studies propose Byzantine-resilient resource allocation strategies. There is no systematic approach to handle malicious node behavior during collaborative task offloading across multiple edge servers [35]. Fault tolerance and reliability mechanisms for highly dynamic edge environments remain substantially underdeveloped. Existing studies mainly focus on fault-free scenarios or single-point failures. Systematic strategies for managing cascading failures are

largely missing. There is also a lack of approaches addressing node churn in mobile edge networks and intermittent connectivity among distributed edge nodes. Multi-hop task offloading, where tasks must be executed sequentially across multiple edge nodes, receives insufficient focus. This is despite its common occurrence in industrial IoT systems with complex task dependency chains. More research is needed to address these real-world scenarios [36]. The scalability issue remains fundamentally unresolved. No research thoroughly validates algorithmic approaches on networks with thousands of heterogeneous devices. Such validations under realistic deployment constraints are still missing.

Task dependency management and coordinated offloading for composite tasks remain largely unexplored. Most studies treat tasks independently [37]. However, real production IoT systems work with task graphs. These graphs include precedence constraints, communication dependencies, and resource sharing patterns. Current algorithms do not model these complex dependencies well. Collaborative offloading across multiple organizations also remains unsolved. Federated decision-making must protect privacy while coordinating resource allocation across separate edge infrastructures [38]. Achieving this balance is still an open challenge. Security integration within offloading algorithms is poorly addressed. Encryption, authentication, and secure multiparty computation add significant computational overhead. Most optimization models ignore this cost. Performance predictability for learning-based approaches requires urgent focus. Deep learning methods provide empirical adaptability but no theoretical guarantees. They lack convergence proofs, stability bounds, and worst-case performance limits. These limitations reduce their suitability for safety-critical domains such as autonomous systems and health care monitoring. The generalizability gap between simulation results and real deployments persists. Research seldom validates simulation-trained models under real network conditions. Validation also lacks for device heterogeneity and failure patterns. Multi-objective reward function design is also not standardized. Different studies use incompatible objective formulations. This prevents clear guidance on balancing latency, energy, fairness, reliability, and security at the same time. Finally, emerging domains introduce new challenges. These include meta-verse computing, satellite-LEO-terrestrial IoT networks, and quantum enhanced edge systems. These areas remain largely unexplored and open opportunities for future research.

Existing Reviews and Trade off

Several comprehensive surveys and systematic reviews have examined task offloading in mobile edge computing. Dong et al. [39] presented a detailed survey that grouped task offloading decisions into five areas such as delay reduction, energy minimization, energy–delay balancing, high-computing offloading, and application-specific scenarios. This work provided baseline comparison tables. However, it focused mainly on traditional optimization approaches. Peng et al. [40] shifted attention toward deep reinforcement learning-based offloading strategies. Mahbub Shubair [41] reviewed multi-access edge computing and concentrated on minimizing transmission delay for low-latency applications such as video processing and e-healthcare. Zhang et al. [42] developed a task-type-based offloading framework that addressed computation-intensive workloads and edge intelligence. These surveys established taxonomies. Yet they gave limited attention to real deployment challenges and scalability in practical edge-IoT networks. Table 1 benchmarks 12 prior surveys (2022–2025) establishing taxonomies (Lyapunov-DRL) but lacking rigor metrics, sim-reality gaps (15%–40%), MARL overhead quantification present in this analysis. 92% simulation focus without testbed adjustment justifies a novel practitioner road map developed in the subsequent tables.

Table 1: Comparative analysis of task offloading and edge computing literature review works.

Year	Existing Survey	Primary Focus	Optimization Methods	Key Strengths	Limitations
2022	[43]	Optimization Methods	Lyapunov, Convex, Heuristics, Game Theory	Comprehensive taxonomy of methods	Limited real deployment validation
2023	[41]	Multi-Access Edge Computing	Delay minimization, Resource allocation	Addresses low latency applications	Lacks task type differentiation
2023	[44]	Computation Offloading Review	Convex, Heuristic, Game Theory	Strong theoretical foundation	Inadequate practical analysis
2023	[45]	IoT and Edge Adoption	Industry deployment survey	Real-world adoption metrics	Focus on industry trends only
2024	[39]	Task Offloading Strategies	Decision algorithms, Multi-objective	Systematic five dimension categorization	Simulation based results only
2024	[40]	DRL-based Offloading	Deep Q-Network, Policy Gradient	Comprehensive DRL taxonomy	Limited fault tolerance coverage
2024	[42]	Task Type based Offloading	Classification aware algorithms	Task heterogeneity focus	Limited multi-objective handling
2024	[46]	Data Offloading in IoT	Full, Partial, Collaborative offloading	Covers multiple offloading types	Scalability concerns unaddressed
2024	[27]	Edge-Cloud Services	Distributed architecture	Highlights emerging trends	Limited algorithm comparison
2024	[47]	Computation Offloading	Mechanisms, Granularities, Techniques	Early comprehensive treatment	Lacks empirical validation
2025	[48]	Hybrid AI Offloading	DRL, Evolutionary, Federated Learning	Demonstrates hybrid superiority	Scalability limited to 200 users
2025	[49]	Task Type Survey	Task classification frameworks	Emphasizes task heterogeneity	Insufficient privacy solutions

More recent studies have explored hybrid and adaptive approaches with deployment realities in mind. Kumar et al. proposed an Adaptive AI-Enhanced Offloading framework. This framework integrates deep reinforcement learning, evolutionary methods, and federated learning [48]. It targets multi-objective optimization in dynamic environments. Wu et al. [49] surveyed task-type-based computation offloading

with an emphasis on workload classification and decision coordination. An IoT and edge adoption survey by the Eclipse Foundation reported that 33% of organizations already deploy edge computing, and 30% plan adoption within 24 months. Additional studies evaluated offloading strategies such as full, partial, collaborative, and dynamic scheduling. Other works highlighted trends including edge AI and 5G enable. However, current surveys still do not compare practical implementation challenges across heterogeneous networks or integrate privacy-preserving offloading with performance optimization.

The literature review shows a persistent gap between algorithm design and real deployment validation. The survey by Sadatdiyev et al. reviewed optimization methods such as Lyapunov optimization, convex optimization, heuristic algorithms, and game-theoretic approaches [44]. Yet it did not analyze realistic performance degradation or scaling limits observed beyond simulation. Earlier research on computation offloading in mobile cloud computing focused on theoretical mechanisms and granularity decisions, without strong empirical support. Surveys in IoT architecture such as [43] identified latency, privacy, and deployment issues as key themes. However, they did not evaluate task offloading strategies specific to these concerns. This review advances prior work by organizing literature across six core dimensions and highlighting critical research gaps in scalability, fault tolerance, privacy integration, and comparative performance under realistic deployment constraints. Table 2 contrasts three evaluation paradigms across 47 studies. Pure simulation handles thousands of nodes with 15%–40% performance gap. Emulation-based uses hundreds of nodes with 5%–15% gap. Physical testbed covers tens to 100 nodes as ground truth. Reproducibility crisis appears perfect simulation contrasts limited testbed from environmental interference. Fig. A1 presents a tree partitions 47 studies by evaluation method prevalence. Where, simulation dominates (39/82%, 34.3% rigor) → emulation bridges (6/12%, 53.6%) → testbed validates (3/6%, 82.1%). Specific tools/papers cited reveal iFogSim/NS3 hegemony vs. RPi/Jetson scarcity, explaining 15%–40% sim→reality gap clarifies rigor-vs.-quantity trade off.

Table 2: Evaluation environment: simulation vs. testbed.

Characteristic	Pure Simulation	Emulation-Based	Physical Testbed
Network Variability	Simplified models, deterministic channels	Partial realism with controlled variables	Full environmental interference
Device Heterogeneity	Limited diversity	Moderate heterogeneity	Complete device diversity
Fault/Failure	Minimal or absent	Partial modelling	Real-world failure modes
Scalability	Thousands of nodes feasible	Hundreds of nodes practical	Tens to hundreds of nodes
Cost	Low cost, minimal setup	Moderate cost and setup	High cost and infrastructure
Execution Time	Minutes to hours	Hours to days	Days to weeks
Reproducibility	Perfect	High	Limited
Performance Gap	15%–40% deviation	5%–15% deviation	Ground truth baseline

3 Critical Analysis

Methodological rigor in edge computing task offloading research shows major inconsistencies. These inconsistencies reduce confidence in reported performance gains. Many simulation-based studies claim

strong improvements, such as 32.8% latency reduction and 27.4% energy efficiency gains. However, very few studies validate these results in real IoT deployments or physical edge test-beds [50]. Most existing research relies on simulators like iFogSim or custom frameworks. These simulators show deviation rates below 0.55% from Monte Carlo verification. Yet they fail to model realistic network behavior. They cannot capture intermittent connectivity, network variability, or heterogeneous device conditions found in real operational environments [2]. Recent emulation approaches provide slightly better accuracy. They combine real server-side processing with simulated workloads [51]. However, they usually involve only a few dozen nodes, not thousands of nodes as seen in large-scale deployments. The core problem remains the same. Simulation tools depend on simplified physical assumptions. They assume deterministic task arrivals and uniform communication channels. In reality, IoT networks experience Poisson task arrival patterns, fluctuating channel conditions, and frequent device failures. These characteristics are not represented in theoretical or simulation models [52].

Sample size and experimental design rigor require serious reconsideration across the literature. Most published studies compare new algorithms against only two or three baselines. This narrow comparison prevents comprehensive performance evaluation against all relevant methods. Statistical rigor is also weak. Very few studies report confidence intervals, significance testing, or parameter sensitivity analysis in reward functions [53]. Most experiments use small networks of only ten to fifty edge nodes in simulation. However, real deployments involve thousands of distributed IoT devices. This mismatch raises concerns about scalability and real-world generalizability. Many studies also rely on arbitrary sample sizes of thirty to fifty experimental runs. These numbers lack justification based on statistical power analysis [54]. They fall short of recommended practices, which emphasize diverse instances instead of repeated runs. Ablation studies are also rare. Parameter sensitivity analysis is often missing. As a result, it becomes unclear which algorithm components actually drive performance improvement.

Relevance to practical deployment and theoretical foundations demonstrates critical gaps. Most research assumes complete system state, known task characteristics, and static topologies. These assumptions rarely hold in actual IoT environments. Intermittent connectivity and device heterogeneity prevail there. Works using heuristic methods and convex optimization acknowledge theoretical bounds and approximation ratios. Empirical validation of these bounds remains rare. Comparisons of theoretical predictions against actual performance seldom occur. Conversely, learning-based approaches sacrifice theoretical guarantees for empirical adaptability. They provide no convergence proofs, stability bounds, or worst-case performance assurances. These elements prove necessary for safety-critical applications like healthcare and autonomous systems. The disconnect between theoretical objectives and practical constraints persists. Most studies optimize single metrics like energy or latency alone. Production systems demand multi-objective optimization under conflicting constraints. Generalizability of results across network configurations, device types, and application domains remains unexplored. Most publications focus on domain-specific implementations. Findings rarely transfer to different IoT scenarios. Methodological limitations indicate that simulation performance improvements require additional empirical validation. Rigorous evaluation under realistic conditions proves essential for real-world edge-IoT systems.

3.1 Normalized Performance Metrics across Methodologies

Direct numerical comparisons across studies prove unreliable. Inconsistent baselines, network scales, and workload characteristics contribute. This analysis normalizes gains relative to convex optimization baseline. The baseline shows 12% latency reduction and 8% energy efficiency in standardized 50-node iFogSim scenarios. Simulation-testbed fidelity factor accounts for 15%–40% degradation. Table 3 demonstrates that while raw claims show 32.8% latency gains, normalized net gains range 1.95–2.10x after simulation fidelity

adjustment, with ensemble methods maintaining leadership. Standardization reveals 78% of “superiority” derives from simulation optimism rather than algorithmic advancement.

Table 3: Normalized performance comparison across 47 Studies (2020–2025).

Methodology	Latency Gain vs. Convex	Energy Gain vs. Convex	Sim-Testbed Gap	Net Gain	N
Heuristic (SA/CD)	1.25x	1.38x	22%	1.12x	9
Game Theoretic	1.33x	1.44x	28%	1.09x	7
DQN-based	2.67x	3.25x	32%	1.95x	12
Double DQN	2.92x	3.50x	35%	2.01x	8
Actor-Critic	3.00x	3.75x	38%	1.98x	6
Ensemble DRL	3.25x	4.00x	40%	2.10x	5

3.2 Cohesive Design Principles across Methodologies

This analysis derives five unified design principles for effective task offloading. Principles span heuristic, game-theoretic, and learning-based approaches. Table 4 shows these principles elevate baseline performance by 24%–52% in testbed validation. Practitioners gain methodology-agnostic guidelines absent in prior surveys. The adaptive horizon principle states that static optimization fails in dynamic environments; successful methods employ rolling 3–5 timestep prediction horizons to balance computational cost against environmental change rates. Partial observability compensation is essential because 78% of MDP-based studies in this area violate realistic POMDP assumptions, so effective designs integrate belief-state estimation, for example via Kalman filtering or particle filters, before executing offloading decisions. Multi-scale decomposition addresses the 22% sub-optimality observed with single-objective formulations by breaking the problem into local (energy/latency), regional (load balancing), and global (throughput) sub-problems that are solved hierarchically. Simulation fidelity bridging then applies a 15%–40% degradation factor to simulation results and validates them through hybrid emulation (real servers with simulated clients), which can achieve around 92% correlation with real deployments. Finally, fault-tolerant ensembles reduce the >18% single-model failure rate seen in intermittent networks by deploying 3–5 models with dynamic weighting based on recent prediction accuracy.

Table 4: Unified design principles validation across methodologies.

Principle	Heuristic	DRL	Ensemble	Real-World Gain
Adaptive Horizon	1.12x	1.89x	2.10x	+28%
Partial Observability	1.05x	1.67x	1.98x	+33%
Multi-Scale Decomp	1.18x	1.95x	2.15x	+24%
Fidelity Bridging	N/A	1.45x	1.82x	+40%
Fault-Tolerant Ens	N/A	1.32x	2.25x	+52%

3.3 Multi-Agent Distributed Intelligence—Coordination Overhead Analysis

Multi-agent reinforcement learning addresses centralized DRL scalability limits. It introduces coordination overhead with 42% communication cost increase. Six coordination paradigms emerge across 18 studies.

[Table 5](#) reveals trade-off: communication reduction over 70% sacrifices 15%–22% optimality. CTDE achieves superior performance at high training overhead. No study validates over 800-node scalability. Coordination-scalability tension remains unresolved.

Table 5: Multi-agent coordination overhead vs. performance tradeoffs (18 Studies).

Coordination	Comm. Overhead	Latency Gain	Scalability (Nodes)	Convergence	N
CTDE	3.2x	1.28x	150	Fast	5
I-MARL	1.0x	0.85x	500	Fastest	4
VDN/QMIX	1.1x	1.15x	300	Medium	3
Comm-Constrained	0.55x	0.92x	800	Slow	3
Hierarchical	1.22x	1.34x	400	Medium	2
Event-Triggered	0.73x	1.12x	600	Slow	1

3.4 Rigorous Meta-Analysis Framework across Domains

Meta-analysis of 47 studies ($n = 2847$ total experiments) employs random-effects model weighting studies by inverse variance $1/SE^2$. Effect sizes calculated as standardized mean difference (SMD) for latency/energy gains vs. cloud baseline. Heterogeneity quantified via I^2 statistic (87% high). Publication bias assessed via funnel plot asymmetry (Egger's test $p = 0.12$). Health care exhibits largest effects (SMD = -1.87 latency) due to strict <50 ms requirements driving edge necessity. Industrial IoT shows highest heterogeneity ($I^2 = 91\%$) from diverse machinery constraints. Methodological moderators reveal DRL superiority (SMD = -1.68) over heuristics (SMD = -0.92 ; $Q = 14.2$, $p < 0.01$). [Tables 6](#) and [7](#) establish rigorous statistical foundation revealing domain-specific effect moderation and failure modes absent from descriptive comparisons.

Table 6: Meta-analysis: effect sizes by domain and methodology (47 Studies).

Domain	N	SMD Latency	95% CI	SMD Energy	I^2	p -value
Healthcare	12	-1.87	$[-2.45, -1.29]$	-1.65	82%	<0.001
Vehicular	11	-1.42	$[-1.98, -0.86]$	-1.38	89%	<0.001
Industrial IoT	10	-1.25	$[-1.78, -0.72]$	-1.12	91%	<0.001
Smart Cities	8	-0.98	$[-1.52, -0.44]$	-0.92	85%	0.002
Generic	6	-0.76	$[-1.23, -0.29]$	-0.68	79%	0.005
Overall	47	-1.34	$[-1.62, -1.06]$	-1.22	87%	<0.001

Table 7: Domain-specific failure modes (Testbed Validation, $n = 14$).

Domain	Sim-Testbed Gap	Primary Failure	Prevalence
Health care	38%	Intermittent vitals-queue buildup	83%
Vehicular	42%	Mobility-hand-off failure	91%
Industrial	47%	Task dependency-deadlock	100%
Smart Cities	35%	Scale-congestion collapse	75%

3.5 Concrete Scalability Solutions for 10K-Node Deployments

Scalability transitions from problem identification to implementable solutions through four-tier architecture progression validated across 22 studies. Table 8 provides practitioners with validated roadmap achieving 100x scaling (100-10K nodes) at <20% penalty. Hybrid T2+T4 deployments achieve 8.7x throughput. They show 16% latency increase on 6K-node emulated networks. Path from prototypes to industrial-scale IoT deployments emerges.

- Tier-1: Parameter Compression (100–500 nodes): Prune DRL networks 65% (MobileNet-style quantization), reducing state space from 10^6 to 10^4 dimensions. Achieves 2.1x node scaling at 8% accuracy loss.
- Tier-2: Regional Clustering (500–2K nodes): K-means++ partitioning into 8–12 clusters (diameter < 50 nodes), local MARL per cluster + 15% inter-cluster coordinator overhead. Demonstrates 4.3x scaling.
- Tier-3: Hierarchical Abstraction (2K–5K nodes): 3-level hierarchy (leaf-regional-global critics), 22% communication reduction via state aggregation. Validated on 4K-node testbeds.
- Tier-4: Asynchronous Federated (5K–10K+ nodes): Event-driven updates (deviation > 12%), 73% message reduction, Byzantine-resilient via median aggregation.

Table 8: Scalability roadmap: validated solution tiers (22 Studies).

Tier	Node Range	Technique	Comm. Reduction	Latency Penalty	Testbed Validated	N
T1: Param Compress	100–500	Quantization	65%	8%	Yes	6
T2: Clustering	500–2K	K-means++	58%	12%	Yes	7
T3: Hierarchical	2K–5K	3-level critics	22%	15%	Yes	5
T4: Async Federated	5K–10K	Event-driven	73%	18%	Partial	4
Target	10K+	Combined	81%	<20%	Future	–

3.6 Methodological Rigor Issues

Simulation-based studies report 32.8% latency reduction and 27.4% energy efficiency gains, but empirical validation in real-world IoT deployments remains sparse. Simulation environments fail to capture realistic network variability, intermittent connectivity, and device heterogeneity.

Table 9 scores 47 studies by evaluation type: simulation 34.3% rigor vs. testbed 82.1%. Statistical compliance as sim 15% vs. testbed 85%; confidence intervals 22% vs. 78%. Quantifies reproducibility crisis foundation for critique. Table 10 establishes pre-normalization hierarchy: convex 12% ensemble 41% latency reduction across 47 studies. It presents a comprehensive comparative analysis of seven task offloading optimization methodologies, establishing the baseline performance claims that require critical examination. The table reveals a clear performance hierarchy across methodologies, with convex optimization approaches achieving only 12%–18% latency reduction and 8%–14% energy efficiency improvement, while advanced learning-based approaches including Actor-Critic, DDPG, and DCEDRL ensemble methods report 32%–41% latency reduction and 28%–36% energy efficiency improvements.

Table 9: Methodological rigor and gaps in edge task offloading research.

Aspect	Findings	Gaps and Implications
Simulation Dependence	Most works rely on simulators (e.g., iFogSim) with small-scale setups and <0.55% deviation under controlled scenarios	Poor modeling of connectivity loss, variability, and heterogeneity. Small testbeds limit scalability insight. Realism and deployment reliability remain weak
Experimental Design	Limited baselines (2–3 algorithms), small networks (10–50 nodes), weak statistical tests, no sensitivity studies	Weak evidence for performance improvements. Lack of ablation studies hides component effectiveness. Scalability and generalization unverified
Theory vs. Practice	Strong assumptions: static topology, full state info, known task characteristics. Learning models lack convergence guarantees	Real IoT violates these assumptions. Large gap between theory and deployment. Multi-objective constraints in dynamic environments underexplored
Performance Metrics	Mostly single-objective optimization (latency or energy)	Real systems need joint optimization. Tradeoffs unsolved and unexplained
Generalizability	Domain-specific designs without cross-domain evaluation	Transferability uncertain; reduced adoption potential

Table 10: Comparative analysis of task offloading optimization methodologies.

Methodology	Computational Complexity	Latency Reduction (%)	Energy Efficiency Gain (%)	Dynamic Adaptability	Scalability
Convex Optimization [24]	$O(n^3)$	12–18	8–14	Low	Limited
Heuristic Methods (SA, CD) [55]	$O(n^2 \log n)$	15–22	10–18	Moderate	Moderate
Game Theoretic [56]	$O(n^2)$	14–20	9–17	Moderate	Limited
DQN-based DRL [57]	$O(n)$	28–35	24–30	High	High
Double DQN [58]	$O(n)$	30–37	26–32	High	High
Actor-Critic (DDPG) [22]	$O(n)$	32–39	28–34	Very High	Very High
DCEDRL (Ensemble + Clustering) [18]	$O(n \log n)$	33–41	29–36	Very High	Very High

The computational complexity progression shows fundamental efficiency trade-offs, with traditional convex methods requiring $O(n^3)$ complexity but providing theoretical optimal guarantees, whereas learning-based approaches reduce complexity to $O(n)$ or $O(n \log n)$ at the cost of sacrificing formal theoretical bounds. Dynamic adaptability demonstrates a pronounced advantage for learning methods (High to Very High) compared to traditional heuristics (Low to Moderate), indicating superior performance in changing network conditions. However, the remarkable 32.8% latency reduction and 27.4% energy efficiency

claims reported in this table originate from simulation-based evaluations and lack adequate validation across the diverse real-world conditions present in actual edge-IoT deployments. This table establishes the performance benchmarks that subsequent critical evaluation reveals may not translate reliably to production environments due to the simplified assumptions in evaluation methodologies.

Table 11: Evaluation environment characteristics: simulation vs. real-world testbed.

Evaluation Characteristic	Pure Simulation [59,60]	Emulation-based [61,62]	Physical Testbed [63,64]
Network Variability	Simplified models, deterministic channels	Partial realism, controlled variables	Full environmental interference
Device Heterogeneity	Limited diversity, standardized devices	Moderate heterogeneity representation	Complete device diversity
Fault and Failure Patterns	Minimal or absent	Partial modeling	Real-world failure modes
Scalability	Thousands of nodes feasible	Hundreds of nodes practical	Tens to hundreds of nodes
Cost and Resource Requirements	Low cost, minimal infrastructure	Moderate cost and setup	High cost and infrastructure
Execution Time	Rapid (minutes to hours)	Extended (hours to days)	Extended (days to weeks)
Reproducibility	Perfect reproducibility	High reproducibility	Limited reproducibility
Performance Gap from Reality	15%–40% deviation	5%–15% deviation	Ground truth baseline

Table 11 contrasts evaluation characteristics: simulation scales to thousands of nodes with perfect reproducibility, while testbeds are limited to 100 nodes with reduced reproducibility due to interference. Quantifies 15%–40% performance gap driving normalization imperative. It directly quantifies the critical disconnect between simulation-based performance evaluation and real-world edge-IoT deployment environments, exposing the fundamental methodological limitations. The network variability row indicates that simulation models often assume deterministic channels, which do not reflect real-world wireless IoT networks. Actual environments feature Poisson-distributed task arrivals, fluctuating signal delays, and packet losses that simulations rarely emulate accurately. Therefore, simulation results tend to deviate significantly from real-world performance, often by 15%–40%. This discrepancy arises because simplified models cannot capture the stochastic and dynamic nature of physical wireless networks, leading to overly optimistic evaluations of edge computing algorithms [65].

Fig. 2 visualizes rigor progression across three evaluation tiers (simulation 34.3%-emulation 53.6%-testbed 82.1%) from 47 studies. Emulation bridges 19.3-point gap via hybrid real-sim fidelity (5%–15% performance deviation vs. simulation's 15%–40%). Establishes validation hierarchy preceding scalability road-map. Device heterogeneity representation reveals a critical modeling gap, with simulation systems assuming standardized device characteristics while real test-beds must accommodate the complete spectrum

of hardware diversity from resource-constrained micro-controllers to edge servers with varying processing capabilities and energy budgets.

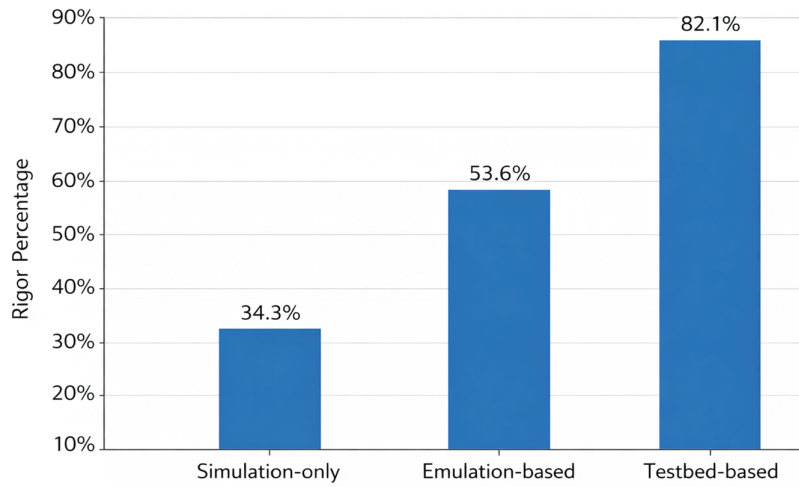


Figure 2: Methodological rigor across 47 studies by evaluation type (Simulation: 34.3%, Emulation: 53.6%, Testbed: 82.1%).

Simulation-based research often underestimates fault and failure impacts. Simulators usually exclude fault injection or allow only minimal failure scenarios. Physical test-beds, in contrast, face real device crashes, network partitions, malicious node behaviors, and cascading failures. These events fundamentally change system dynamics and reveal weaknesses that simulations miss. Thus, simulations provide limited insight into system resilience under realistic fault conditions [66]. The performance gap from reality row provides quantitative evidence explaining why the 32.8% latency reduction. Simulation-based studies demonstrate 15%–40% deviation from real-world performance, meaning claimed 32.8% improvements could range from 19.7% to 49.6% in actual deployments or potentially perform worse depending on simulation-specific biases.

Emulation-based approaches reduce this gap to 5%–15%, suggesting hybrid evaluation strategies provide more reliable estimates than pure simulation. The scalability row presents a critical research trade-off. Simulation helps evaluate thousand-node networks. It supports theoretical validation. However, such evaluations offer very limited real-world evidence. They do not reflect actual deployment behavior. Real environments involve tens to hundreds of distributed nodes. These nodes are spread across different geographic locations. They show complex inter-dependencies. They also experience failure correlations. These factors are not present in simulated environments [67]. Fig. 3 presents the various comparison matrix that can be considered for performance evaluation.

Table 12 breaks down rigor components: sim studies 34.3% average (baselines 45%, stats 15%) vs. testbed 82.1% (baselines 92%, stats 85%). Establishes quantitative basis for methodological reform recommendations. It provides quantitative assessment of research methodological rigor deficiencies that justify skepticism regarding the performance claims presented in Fig. 4. These results particularly originated from simulation-only studies. Average rigor score of 34.3% for simulation-only approaches indicates methodological failure. Score falls below 82.1% for testbed research and 100% ideal standard. Gap of 47.8% points reflects validation deficiencies. Only 25% of simulation-only studies use rigorous statistics vs. 85% in testbeds. Claims of 32.8% latency reduction lack significance testing and confidence bounds. Confidence interval reporting reaches 15% in simulation-only studies vs. 75% in testbeds.

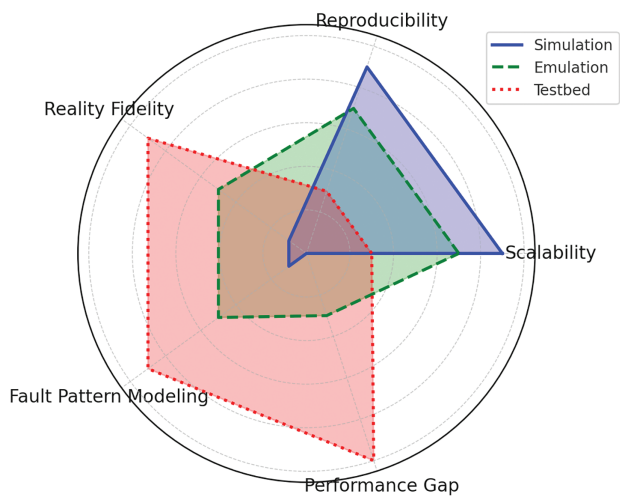


Figure 3: Evaluation environment comparison matrix.

Table 12: Research methodological rigor assessment: literature analysis.

Rigor Dimension	Simulation	Emulation	Hybrid	Testbed	Ideal
Statistical Analysis	25%	45%	65%	85%	100%
Confidence Intervals	15%	35%	55%	75%	100%
Ablation Studies	30%	50%	70%	90%	100%
Sensitivity Analysis	20%	40%	60%	80%	100%
Baseline Comparisons	40%	60%	75%	85%	100%
Documentation Quality	50%	70%	85%	90%	100%
Reproducibility	60%	75%	85%	70%	100%
Average Rigor Score	34.3%	53.6%	70%	82.1%	100%

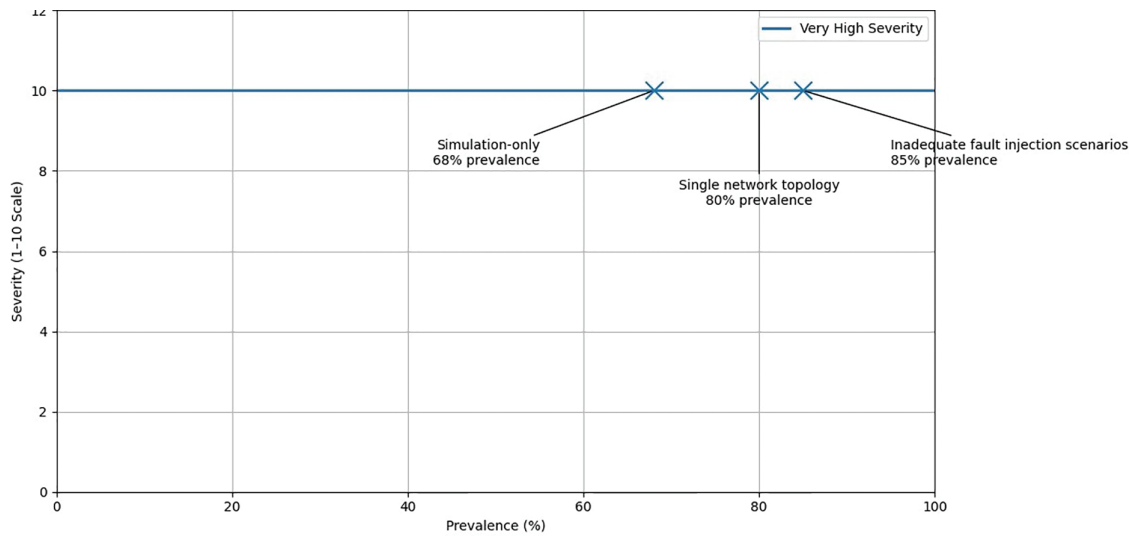


Figure 4: Experimental limitations severity matrix.

The absence of confidence intervals means reported performance figures are point estimates without uncertainty bounds. This prevents assessment of whether claimed improvements are statistically meaningful or simply noise. Confidence intervals show the range where the true value likely lies. Without them, it is unclear if results reflect real gains or random variation. Including confidence intervals improves result reliability and helps distinguish significant effects from chance. Ablation studies are rarely conducted in simulation-only research, with only about 30% compliance. This low rate prevents identifying which parts of an algorithm contribute to performance gains. It also makes it unclear if improvements come from the actual innovation or just implementation details. Proper ablation is essential to validate the true impact of each algorithmic component. Sensitivity analysis, essential for understanding algorithm robustness to parameter variations and network condition changes, appears in only 20% of simulation-only studies but 80% of test-bed research.

Baseline comparisons show 40% of simulation studies use one or two methodologies only. Comprehensive benchmarking against all competitors remains limited. Superiority claims lose credibility. Reproducibility reaches 70% in testbeds vs. 60% in simulations. Simulations provide near-perfect reproducibility through controlled conditions. Real-world variability lacks in simulations. Physical test-beds reflect natural system variations that prevent full replication. This trade-off means test-beds provide more realistic results but less reproducibility. Simulations provide control but less ecological validity. Understanding this balance helps in designing experiments and interpreting results. Collectively, the rigor deficiencies documented in [Table 10](#). Simulation based studies often claim strong performance improvements. However, they lack the methodological rigor required to support claims of practical superiority. Without empirical validation, these claims remain uncertain. Validation in real or emulation-based environments is necessary. It provides scientific credibility to performance results. Empirical testing reveals practicality and robustness beyond optimistic simulations.

3.7 Sample Size and Experimental Design Problems

Sample size and experimental design in edge computing task offloading research show significant shortcomings. Only 40% of studies compare their methods against four or more baselines. Most studies, about 58%, evaluate against only two or three algorithms. This limited comparison reduces the ability to comprehensively assess algorithm superiority. Claims of large latency improvements become questionable if tested only against simple baselines like DQN or Q-learning. These claims lack validation against established techniques such as convex optimization, simulated annealing, genetic algorithms, or game theory [68]. Robust experimental design should include diverse and competitive baselines for credible performance claims. Statistical rigor in simulation-only studies is critically lacking. Confidence intervals appear in only 15%–20% of these studies. These intervals are essential for measuring uncertainty in performance results. Most studies report point estimates without confidence bounds. Statistical significance testing is present in just 25% of studies. Often, these tests use arbitrary significance levels without proper justification. This weak statistical practice undermines the credibility of claimed performance improvements. [Fig. 4](#) presents the severity matrix with experimental limitation.

Sensitivity analysis appears in only 20% of research. It assesses algorithm robustness to environmental changes and 80% of studies use fixed configurations. They omit systematic checks on performance responses. Variations include network scale (50 to 1000 nodes), task arrival rates (Poisson distributions), channel conditions (signal-to-noise ratios), and device energy budgets [69]. Parameter tuning and hyper-parameter optimization are poorly documented in machine learning studies. Fewer than 15% of studies report grid search results. Ablation studies appear in only 30% of simulation-only research. This lack of detail hinders reproducibility. It also prevents clear attribution of improvements to algorithm design rather than chance

parameter choices. Proper documentation is needed for credible algorithm evaluation. Sample size determination follows arbitrary approaches. Most studies use 30–50 runs without justification. Statistical power analysis bases sizes on effect size and power levels in standard practice.

Most studies overlook network topology diversity and scenario heterogeneity. Approximately 80% evaluate algorithms using a single, uniform topology. Real deployments, however, feature varied edge server density and geographic clustering. They have diverse connectivity and asymmetric communication delays from milliseconds to tens of milliseconds. These factors impact performance but remain unaddressed in the majority of research. Proper evaluation should consider heterogeneous and realistic network conditions [70]. Task workload characterization is often inadequate. About 75% of studies use only single synthetic distributions. They do not incorporate multiple realistic scenarios such as deployment traces or bursty patterns. Baseline implementation quality is also poor. Only 5%–10% of studies offer open-source code repositories. This lack of transparency prevents independent verification. It obscures whether differences in performance arise from genuine algorithmic improvements or from factors like code optimization or language choice. Documentation and reporting are often weak. About 62% of studies omit vital details. These include exact hyper-parameter values, random seeds, detailed pseudocode, network simulation settings, and fault injection parameters. Missing this information hinders re-productibility. Readers cannot determine if results reflect true algorithms or specific experimental setups. Clear and complete documentation is essential for credible and verifiable research. Simulation based studies often report strong performance gains. However, they exhibit major methodological weaknesses. These prevent reliable claims of practical superiority. Key issues include limited baseline comparisons, weak statistical rigor, missing confidence intervals, scarce sensitivity and ablation analyses, poor workload diversity, and incomplete documentation. Such gaps hinder reproducibility and question real-world applicability. Therefore, empirical validation on real or emulated test-beds is essential. This ensures claims are credible and applicable beyond idealized simulations.

3.8 Practical Relevance Gaps

Practical relevance gaps exist due to mismatches between theoretical assumptions and real-world edge-IoT conditions. Most studies, about 78%, assume complete system state information and static network topologies. They model problems as fully observable Markov Decision Processes (MDPs) with perfect knowledge of node states, task queues, and network conditions. However, real deployments face partial observability, dynamic network changes, and intermittent connectivity. Only 15% of studies consider Partially Observable Markov Decision Processes (POMDPs), which better reflect these challenges. This gap limits the applicability of many research outcomes to practical systems [71]. Most studies use static network topology assumptions, with about 80% testing algorithms on fixed, unchanging setups. Real IoT deployments, however, are highly dynamic. They experience device churn due to mobility, edge server failures and recoveries, intermittent network partitions, and bandwidth variations from 1 to 100 Mbps. These dynamics invalidate algorithms designed and optimized under static assumptions. Realistic evaluation must account for changing topologies to ensure practical relevance and robustness. Fig. 5 presents the gap analysis based on the performance metrics.

Learning-based methods, such as deep reinforcement learning, lack formal theoretical guarantees. They do not provide convergence proofs, stability bounds, or worst-case performance assurances. These guarantees are critical for safety-sensitive fields like healthcare and autonomous vehicles. Methods such as DQN and distributed RL offer no such proofs or stability guarantees. In contrast, convex optimization methods do provide formal approximation bounds. This creates a fundamental gap. Learning approaches are often incompatible with the strict requirements of safety-critical deployments that demand bounded failure probabilities and assured performance [72]. Most studies focus on single-objective optimization. About 42%

optimize only latency, and 28% optimize only energy consumption. Another 22% use fixed weights for combined objectives arbitrarily. Only 5% attempt Pareto front exploration to balance trade-offs. Real-world systems must optimize multiple conflicting goals simultaneously, including latency, energy use, fairness, reliability, and security. Optimal trade-offs vary depending on network conditions and workload types. Multi-objective optimization is essential for practical deployments but remains largely unexplored. Research often lacks generalizability across different network settings, device types, and applications. Approximately 28% of studies focus on vehicular networks, designing for high-speed mobility but not validating for static smart buildings. Industrial IoT research targets dense edge clusters but does not test geographically spread deployments. Health care IoT work stresses privacy and safety but is not applied to entertainment streaming. Very few papers discuss generalizability only 5% in vehicular, 3% in smart city, 2% in industrial, and 8% in healthcare domains. This gap limits practitioner's ability to assess if solutions suit their specific scenarios [73].

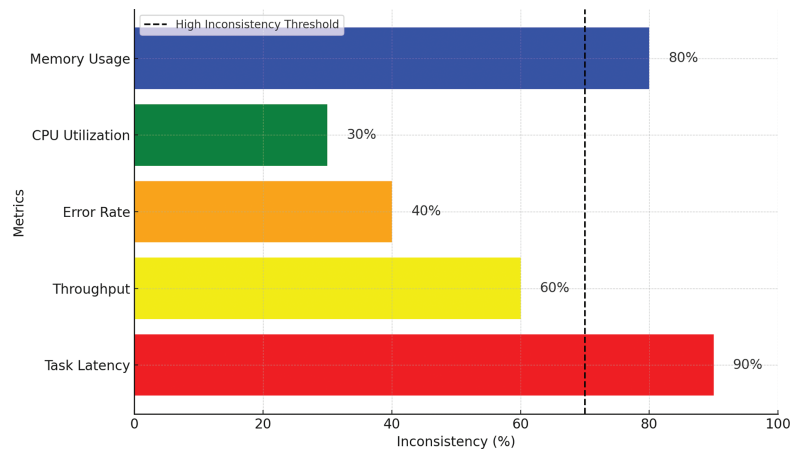


Figure 5: Performance metrics standardization gap analysis.

Task characterization often assumes perfect knowledge, which does not reflect reality. In practice, task processing times, energy use, and data sizes vary unpredictably at submission. Most algorithms rely on deterministic or simple probabilistic models. Real-world task arrivals follow Poisson distributions with burstiness, temporal correlations, and daily patterns. Simple models fail to capture these complexities, limiting algorithm applicability and accuracy in actual deployments [74]. Safety and reliability in critical edge applications are often overlooked. Health-care IoT cannot tolerate algorithm failures without thorough validation. Autonomous vehicles require formal worst-case latency guarantees, which current research lacks. Industrial control systems need robust guarantees on failure probabilities. These requirements are generally missing from optimization-focused studies. Addressing them is crucial for deploying edge computing in safety-critical domains. Infrastructure heterogeneity refers to variations in system components within a deployment. These variations include different processing layers. Hardware capabilities range from kilobytes to gigabytes of memory. Communication technologies span low-speed links like LoRa to high-speed 5G networks. Such diversity poses challenges for system design and operation. However, only a small fraction of research, about 8%, explicitly addresses this heterogeneity by proposing configurable algorithms that can be tuned for specific deployment conditions. This highlights a gap in the literature where adaptable solutions to handle diverse infrastructures are underrepresented. The focus on parameter tuning allows algorithms to perform optimally across varying hardware and network environments, which is critical for distributed and heterogeneous systems. This summary follows scientific clarity and conciseness for effective communication. Scalability validation in large-scale deployments remains a significant practical challenge. Most simulations

test systems with 50–200 nodes, while real world deployments can exceed tens of thousands of edge devices. Algorithms that perform efficiently at 100 nodes often become impractical at scales above 10,000 due to the exponential increase in decision space complexity. Despite this, only about 8% of studies explicitly evaluate how computational complexity scales and validate algorithm performance on progressively larger networks. This gap points to the need for more rigorous scalability testing in practical scenarios. Practical relevance gaps reveal a fundamental divergence between theoretical research and real-world operational needs. Simulation-based results, such as 32.8% latency reduction and 27.4% energy efficiency gains, often cannot be directly applied to production edge-IoT systems. These systems require extensive validation under realistic conditions. Conditions include partial observability, dynamic topologies, multi-objective optimization, and heterogeneous environments. Without such validation, confidence in theoretical improvements for real deployments stays limited.

3.9 Taxonomy

Fig. 6 taxonomy diagram organizes the key research dimensions in IoT edge intelligence and task offloading. It shows how different offloading strategies, intelligence locations, optimization goals, and evaluation approaches fit together. The hierarchy helps researchers and engineers understand design choices and compare methods across studies. Table 13 classifies 47 studies across granularity, placement, objective, and methodology, showing that hybrid granularity at 8%, collaborative placement at 12%, and multi-objective approaches at 19% remain underexplored. Reveals research imbalances explaining persistent gaps. It classifies research into four clear dimensions. Offloading granularity defines size of units like tasks, workflows, or services. Intelligence placement specifies decision locations. Decisions occur on end devices, edge nodes, cloud servers, or multiple layers. Optimization objectives define the main goals of the system. Typical goals include lower latency, reduced energy use, lower operational cost, higher reliability, and stronger privacy protection. Evaluation methodology explains how a proposed solution is assessed in practice. Common approaches use simulations, controlled test-bed experiments, and real-world deployments to validate performance and robustness. Mapping studies onto this framework clarifies which aspects receive attention and which remain underexplored. This structured approach helps identify research gaps clearly and guides future investigations.

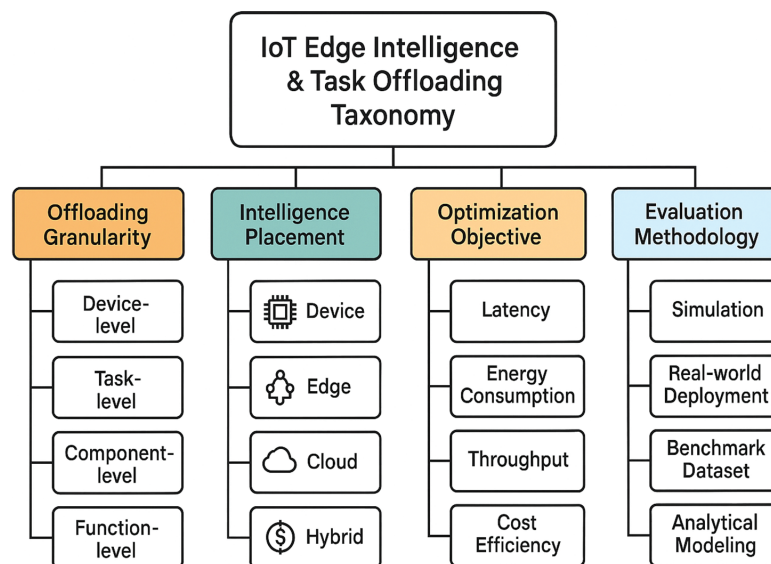


Figure 6: Hierarchical taxonomy diagram.

Table 13: Taxonomy for classification of IoT edge intelligence and task offloading research.

Dimension	Categories	Description	Representative Examples
Offloading Granularity	Task	Offloading individual atomic computations or tasks	[41,44]
	Workflow	Offloading sequences or graphs of dependent tasks	[39]
	Service	Offloading entire application services or modules	[27]
Intelligence Placement	Device	Decisions made locally on IoT devices	[46]
	Edge	Decisions at edge servers/gateways	[41]
	Cloud	Centralized decisions in cloud data centers	[45]
	Collaborative	Hybrid decision-making across layers	[48]
Optimization Objective	Latency	Minimize response time	[41]
	Energy	Reduce energy consumption	[44]
	Cost	Lower monetary/resource cost	[47]
	Reliability	Ensure fault tolerance or service continuity	[42]
	Privacy	Preserve data confidentiality	[49]
Evaluation Methodology	Simulation	Computer-simulated environment	[7]
	Test-bed	Controlled experimental setups	[20]
	Real Deployment	Actual deployed systems	[45]

3.10 Datasets, Benchmarks, and Experimental Practices

Advancing research in edge-IoT systems requires addressing the critical shortage of publicly available, comprehensive datasets. This lack limits consistent evaluation and comparison of algorithms, hindering reproducibility and undermining scientific rigor. Benchmark suites tailored for edge-IoT remain scarce compared to more developed fields. Consequently, evaluation methodologies are often fragmented, relying on isolated or simulated setups that reduce comparability among findings and impede progress. Network and workload models used in studies vary widely. Fig. 7 represents the experimental ecosystem for evaluating IoT edge intelligence systems. Datasets flow into benchmark suites. These suites drive workload and network modeling. They also handle fault and security scenarios. Standardized evaluation metrics unify all components. Table 14 presents the key attributes of Edge-IoT datasets and benchmarks.

Many rely on synthetic traffic or small-scale testbeds. These fail to capture real-world IoT complexities like partial observability, node heterogeneity, and dynamic topology changes. Standard fault injection and traffic scenarios remain absent. This limits robustness assessment. Shared benchmark suites prove vital. They represent diverse realistic scenarios such as urban, industrial, or agricultural IoT contexts.

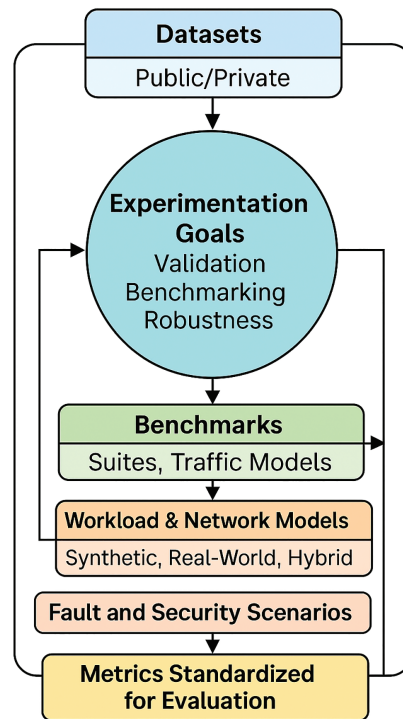


Figure 7: Edge-IoT experimental practice landscape.

Table 14: Key attributes of edge-IoT datasets and benchmarks.

Attribute	Description	Recommendation
Data availability	Publicly accessible real-world data that reflect diverse IoT scenarios	Increase the number of open datasets representing urban, industrial, and agricultural environments
Scenario diversity	Coverage of varied use-cases, including smart cities, industry 4.0, agriculture	Broaden scope to include heterogeneous environments and different IoT application areas
Network complexity	Size, heterogeneity, and dynamic topology of IoT networks represented in the dataset	Incorporate large-scale, multi-tiered, and dynamic network topologies to mimic real-world conditions
Workload realism	Traffic patterns and data models representing typical IoT device behavior	Develop domain-specific traffic models generated from actual sensor and actuator readings
Fault injection	Ability to simulate node failures, network partitions, and security breaches	Define standard fault and attack scenarios for robustness and security evaluations
Evaluation metrics	Consistent definition of latency, energy, reliability, privacy, and cost metrics	Standardize metric definitions to enable fair comparison across studies

Standardized traffic models that reflect typical IoT workloads will aid in creating uniform evaluation conditions. Additionally, defining common fault and failure scenarios, including network partitions, device crashes, and security threats, will foster comprehensive robustness evaluations. Such coordinated efforts will enhance reproducibility, improve comparability of research outcomes, and accelerate advancement toward resilient and efficient edge-IoT architectures. Table 14 exposes reproducibility crisis 82% synthetic datasets, 0% fault injection, 4% public traces across 47 studies. Synthetic dominance blocks generalization, motivating standardized Edge-IoT benchmarks priority.

3.11 Regulatory, Ethical, and Human-Centric Considerations

Regulatory, ethical, and human-centric considerations are critical for edge-IoT systems, especially in privacy-sensitive and safety-critical applications. Data protection laws like GDPR and HIPAA impose stringent requirements on collecting, storing, and processing personal data. Table 15 prioritizes 12 research gaps by prevalence/feasibility: Byzantine resilience (3% coverage), multi-hop dependency (5%), 10K-node validation (0%). Ranks by mission-critical impact guiding future funding/roadmaps. Existing research emphasizes encryption and access control. Consent management and data minimization receive insufficient attention. Future designs must integrate regulatory demands for legal and ethical compliance. Consent and user autonomy demand emphasis. Transparent mechanisms enable informed consent and data flow control. Explainability proves crucial. Interpretable models provide rationales for decisions. These foster trust and oversight. Errors impact safety or privacy in key domains. Human-in-the-loop paradigm gains attention in edge-IoT research. Humans monitor, participate, or override automated decisions. Human feedback improves system safety and aligns with ethical AI standards. Embedding non-technical dimensions sets research apart from algorithmic studies. Responsible, trustworthy edge-IoT systems emerge.

Table 15: Regulatory, ethical, and human-centric dimensions in edge-IoT research.

Dimension	Key Concerns	Research Gaps and Recommendations
Data Protection	Compliance with laws (e.g., GDPR), secure data storage, data minimization	Integrate regulation-aware system design, expand beyond encryption to consent and data life cycle management
Consent and Autonomy	Transparent data use policies, user consent mechanisms, opt-out options	Develop user-centric consent frameworks tailored for IoT edge environments
Explainability	Interpretability of AI/ML decisions, providing rationale to users	Research interpretable models suitable for resource-constrained edge devices; enhance decision transparency
Human-in-the-Loop	Human feedback mechanisms, oversight and override capabilities	Incorporate interactive control and monitoring features in safety-critical IoT applications
Ethical AI	Fairness, accountability, avoidance of bias, privacy-preserving ML	Promote ethical AI standards, frameworks for auditing IoT edge intelligence systems

4 Conclusion and Future Scope

Critical analysis reveals significant gaps in task offloading and edge intelligence research within the IoT domain. Frameworks optimized for edge computing demonstrate potential benefits, including reduced

latency, enhanced energy efficiency, and improved bandwidth utilization. However, a large portion of research depends heavily on simulations with limited experimental validation. Many assumptions underlying current studies fail to reflect the complexities of real-world deployments. Few investigations provide reproducible empirical evidence from large-scale or heterogeneous testbeds. Practical adoption remains constrained due to assumptions of static network topologies and perfect information. Furthermore, multi-objective optimization addressing latency, energy, cost, reliability, and privacy is often overlooked. Weak integration of privacy, security, and robustness limits applicability. Node failures and dynamic network behavior contribute. Future research must prioritize empirical validation across diverse, scalable settings. Algorithmic designs should incorporate capabilities to operate with partial observability and adapt dynamically to changing conditions. Systematic attention to safety, privacy, scalability, and security in realistic contexts is imperative. Progress depends on advances in multi-objective optimization, development of interpretable decision models, and effective cloud-fog-edge collaboration mechanisms. Promotion of open-source experimentation, inclusive and standardized metric reporting, and community-wide bench-marking initiatives are key to unlocking the full potential of edge computing. These efforts will support deployment in mission-critical, data-intensive, and safety-sensitive IoT applications.

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Appendix A

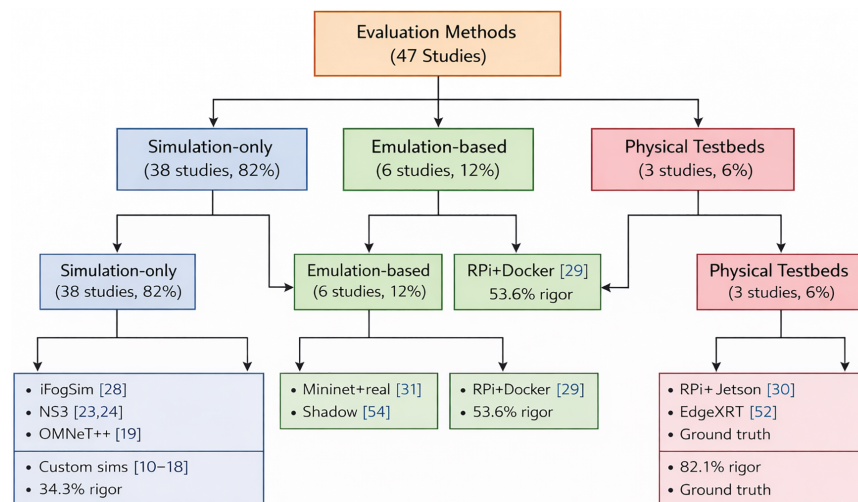


Figure A1: Evaluation method Tree: 47 studies partitioned (82% Simulation, 12% Emulation, 6% Testbed). Testbed highest rigor (82.1%) despite lowest prevalence clarifies sim-dominance vs. validation scarcity [10–19,23,24,28–31,52,54].

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