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Research Article

EDGE COMPUTING AND REAL-TIME DATA PROCESSING: OPTIMIZING LATENCY AND EFFICIENCY IN INTERNET OF THINGS (IOT) ECOSYSTEMS

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Abstract
The rapid expansion of Internet of Things (IoT) ecosystems has intensified the need for efficient real-time data processing, exposing limitations of cloud-centric architectures in handling latency-sensitive applications. Increasing data volumes, network congestion, and delayed response times have highlighted the necessity of decentralized computing approaches. This study aims to examine the effectiveness of edge computing in optimizing latency and system efficiency within IoT environments. A mixed-methods experimental and simulation-based design was employed, comparing edge-based, cloud-based, and hybrid architectures across multiple application scenarios. Performance metrics including latency, throughput, energy consumption, and bandwidth utilization were analyzed using statistical and comparative techniques. Findings indicate that edge computing significantly reduces latency and energy consumption, while hybrid architectures achieve optimal throughput and scalability. Bandwidth utilization emerges as a key mediating factor influencing system performance, with decentralized processing improving responsiveness under high network load conditions. The study concludes that edge computing provides a robust and adaptive solution for enhancing real-time data processing in IoT ecosystems, particularly when integrated with cloud systems through optimized task allocation strategies. Effective deployment requires context-aware design, efficient resource management, and alignment with application-specific requirements.

Keywords: Distributed Systems, Edge Computing, Iot, Latency Optimization, Real-Time Processing

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INTRODUCTION

The rapid proliferation of Internet of Things (IoT) devices has fundamentally transformed digital ecosystems by enabling continuous data generation, interconnected communication, and intelligent automation across diverse domains (Padhiary et al., 2024). Smart cities, industrial automation, healthcare monitoring, and autonomous systems increasingly rely on IoT infrastructures to collect and process vast amounts of real-time data (Liao et al., 2024). Traditional cloud-centric architectures, while powerful in storage and computation, face inherent limitations in handling latency-sensitive applications (Pandiyan et al., 2024). The growing demand for instantaneous data processing and responsiveness has exposed critical performance bottlenecks within centralized computing models.

Edge computing has emerged as a promising paradigm to address these challenges by decentralizing computation and bringing processing capabilities closer to data sources (Abd Al-Alim et al., 2024). By enabling local data analysis at or near the network edge, this approach reduces the need for long-distance data transmission to centralized servers (Feng et al., 2024). Such proximity significantly enhances responsiveness and reduces latency, making it suitable for time-critical applications such as autonomous vehicles, industrial control systems, and remote healthcare services (Yang et al., 2024). The integration of edge computing within IoT ecosystems represents a shift toward distributed intelligence and real-time decision-making.

The increasing complexity of IoT networks further amplifies the need for efficient data management strategies that balance performance, scalability, and resource utilization (Wang et al., 2024). Real-time data processing at the edge introduces new considerations related to computational efficiency, network bandwidth, and system reliability (Sunkari et al., 2024). Ensuring optimal coordination between edge devices and cloud infrastructure is essential for maintaining system integrity and performance (El Sakka et al., 2025). Understanding how edge computing can be effectively leveraged to optimize latency and efficiency is therefore critical for advancing next-generation IoT systems.

Current IoT architectures often rely heavily on centralized cloud computing, resulting in latency issues that hinder the performance of time-sensitive applications (Rahman et al., 2024). Data transmission delays, network congestion, and dependency on remote servers create inefficiencies that compromise system responsiveness (Tian et al., 2024). These limitations are particularly problematic in scenarios requiring immediate decision-making, where delays can lead to operational failures or safety risks (Li et al., 2025). The reliance on cloud-centric models highlights a fundamental mismatch between system design and application requirements.

Edge computing offers potential solutions, yet its implementation introduces new challenges related to resource constraints and system coordination (Sharma et al., 2024). Edge devices typically possess limited computational power and energy capacity, which can restrict their ability to process complex data streams (Tong et al., 2025). Managing distributed processing across heterogeneous devices adds further complexity, particularly in ensuring consistency, reliability, and security (Nie & Rezvani, 2025). These challenges raise questions about the scalability and practicality of edge-based solutions in large-scale IoT deployments.

The absence of standardized frameworks for integrating edge computing with IoT systems further complicates adoption (Sun et al., 2025). Variations in architecture, protocols, and deployment strategies lead to fragmented implementations and inconsistent performance outcomes (K. Singh et al., 2025). Lack of clear guidelines for optimizing latency and efficiency across different contexts limits the effectiveness of current approaches (Mnkash et al., 2024). Addressing these issues requires a systematic investigation of how edge computing can be structured and optimized within IoT ecosystems.

This study aims to analyze the role of edge computing in enhancing real-time data processing within IoT ecosystems, with a focus on optimizing latency and system efficiency (Khanh Quy et al., 2025). The research seeks to evaluate how distributed processing at the network edge influences data transmission speed, computational performance, and overall system responsiveness (Mao et al., 2026). Emphasis is placed on identifying key factors that contribute to performance improvements in latency-sensitive applications.

Another objective of this study is to examine the interaction between edge devices and centralized cloud systems in hybrid computing architectures (Sabuncu & Bilgehan, 2024). The research explores how task allocation, data distribution, and communication protocols affect system efficiency and reliability (N et al., 2025). Attention is given to understanding how edge and cloud components can be integrated to achieve optimal performance (Nemati & Mansouri, 2025). This objective reflects the need to balance decentralization with centralized coordination.

The study also aims to develop a conceptual framework for optimizing edge computing deployment in IoT environments (Neelakantan et al., 2024). This framework is intended to provide practical guidance for system designers, engineers, and researchers in implementing efficient and scalable solutions (Krishnan & Durairaj, 2024). Findings are expected to contribute to both theoretical understanding and practical application of edge computing in real-time data processing (Shu et al., 2024). The objective underscores the importance of advancing intelligent and responsive IoT systems.

Existing literature on IoT and cloud computing has extensively explored centralized data processing models, yet relatively limited attention has been given to the practical integration of edge computing in real-time applications (Zhang et al., 2024). Many studies focus on theoretical advantages of edge computing without providing empirical evidence or comprehensive evaluation of performance outcomes (Jameil & Al-Raweshidy, 2025). This gap limits the ability to assess the true impact of edge-based architectures on latency and efficiency.

Research on edge computing often addresses specific technical aspects such as network optimization or device-level processing, without integrating these components into a unified framework (Ros et al., 2024). Fragmentation of research across different domains results in isolated findings that do not fully capture the complexity of IoT ecosystems (Chauhan et al., 2025). The lack of holistic approaches that consider system-wide interactions represents a significant limitation in current scholarship.

Interdisciplinary studies that combine network engineering, data science, and system architecture perspectives remain underdeveloped (Kau et al., 2025). Existing research may overlook the interdependencies between computational efficiency, data flow, and network performance (S. Singh et al., 2024). The absence of integrative models that connect these dimensions highlights a critical gap. This study aims to address this limitation by providing a comprehensive analysis of edge computing within IoT systems.

This study introduces a novel perspective by examining edge computing as an integrated solution for optimizing both latency and efficiency in IoT ecosystems, rather than focusing on isolated performance metrics (Azevedo et al., 2024). The research emphasizes the importance of coordinated interaction between edge and cloud components, offering a more comprehensive understanding of distributed computing architectures (Abbasi & Hadi, 2024). This approach advances the discourse by linking theoretical concepts with practical implementation strategies.

The study contributes methodologically by combining analytical evaluation with system-level considerations, enabling a multidimensional assessment of performance outcomes. Integration of latency analysis, resource utilization, and network efficiency provides a holistic framework for evaluating edge computing solutions (Liang & Sun, 2024). This methodological contribution enhances the relevance and applicability of the research in real-world contexts.

The justification for this study lies in the increasing reliance on IoT systems in critical applications where performance and reliability are essential (Villegas-Ch et al., 2025). Optimizing latency and efficiency is fundamental to ensuring the success of these systems, particularly in domains such as healthcare, transportation, and industrial automation. Addressing the limitations of current architectures through innovative approaches to edge computing is therefore essential (Alatawi, 2025). This research contributes to the development of more responsive, efficient, and scalable IoT ecosystems.

RESEARCH METHOD

Research Design

This study adopts a mixed-methods experimental and simulation-based research design to evaluate the effectiveness of edge computing in optimizing latency and efficiency within Internet of Things (IoT) ecosystems (Shahid et al., 2025). The robust design integrates quantitative performance testing with system-level modeling to allow for a direct comparison of edge-based, cloud-based, and hybrid architectures under controlled conditions (Kengesbayeva et al., 2025). While experimental evaluation focuses on specific key performance indicators, simulation techniques are simultaneously employed to model large-scale IoT environments and assess system scalability and resource allocation strategies, thereby enabling a comprehensive assessment of both technical performance and system behavior under real-time data processing conditions.

Research Target/Subject

The population of this study consists of IoT devices, edge nodes, and cloud servers operating within simulated and controlled network environments. Sampling is conducted using a purposive and scenario-based approach to accurately represent diverse IoT applications, including smart healthcare, industrial monitoring, and real-time surveillance systems. The experimental setup includes a selected set of sensor devices, edge computing units, and centralized cloud platforms, all specifically configured to emulate real-world deployment conditions. This sampling strategy ensures that the subsequent analysis reflects both essential application diversity and varying operational demands.

Research Procedure

Data collection procedures begin with the initial configuration of experimental environments representing the edge-based, cloud-based, and hybrid architectures. Following this setup, IoT devices generate continuous data streams, which are processed under the different computational models. Data collection involves collecting and recording quantitative performance metrics for each scenario, followed by repeated trials to ensure consistency and reliability. Additionally, simulation experiments are conducted to evaluate system scalability and performance under varying network conditions and workloads, capturing data streams to evaluate performance across these configurations.

Instruments, and Data Collection Techniques

Instruments used in this study include a suite of performance monitoring tools, network simulation software, and analytical frameworks for system evaluation. Specifically, monitoring tools are employed to measure crucial metrics such as latency, bandwidth utilization, processing time, and energy consumption in real time. Network simulation platforms are further utilized to replicate IoT environments and test system behavior under different load conditions and communication protocols. Furthermore, analytical models are developed to evaluate task allocation strategies, while comprehensive data logging systems are implemented to ensure the accurate recording and reproducibility of all experimental results.

Data Analysis Technique

Data analysis is performed using a combination of statistical and comparative techniques to identify specific performance differences and optimization patterns among the studied configurations. The analytical approach focuses on examining the data collected regarding key performance indicators like throughput and task completion time across varying workloads and operational demands. Finally, the integration of both experimental and simulation results allows for a comprehensive evaluation of overall system efficiency and the specific impact on latency reduction.

RESULTS AND DISCUSSION

The dataset integrates performance metrics collected from controlled experiments and large-scale simulations comparing edge-based, cloud-based, and hybrid IoT architectures. Key indicators include end-to-end latency, throughput, energy consumption, task completion time, and network bandwidth utilization. A total of 300 experimental runs were conducted across three application scenarios smart healthcare monitoring, industrial automation, and real-time surveillance. Descriptive statistics reveal consistent performance improvements in edge-enabled configurations, particularly in latency-sensitive tasks.

Table 1. Performance Comparison Across Computing Architectures in IoT Systems

Indicator	Cloud-Based	Edge-Based	Hybrid Model
Average Latency (ms)	120	45	60
Throughput (requests/sec)	850	920	980
Energy Consumption (Joules)	75	52	60
Task Completion Time (ms)	140	70	85
Bandwidth Utilization (%)	88	62	70

Descriptive results indicate that edge-based architectures achieve the lowest latency and energy consumption, while hybrid models demonstrate the highest throughput. Cloud-based systems exhibit higher latency and bandwidth usage due to centralized processing. These findings suggest that distributing computation closer to data sources significantly enhances system responsiveness.

The explanation of these findings highlights that edge computing reduces data transmission distance and network congestion, leading to faster processing times. Lower energy consumption is attributed to reduced reliance on long-distance communication and centralized infrastructure. Hybrid models benefit from combining local processing with centralized resources, optimizing both performance and scalability.

Improved throughput in hybrid architectures reflects efficient task distribution between edge nodes and cloud servers. Edge systems handle time-critical tasks, while cloud infrastructure manages complex computations and storage. This division of labor enhances overall system efficiency and reliability.

Further descriptive analysis across application scenarios reveals that latency reduction is most significant in real-time surveillance systems, where rapid decision-making is critical. Industrial automation systems show notable improvements in task completion time, while healthcare monitoring applications demonstrate enhanced energy efficiency. These variations highlight the context-specific benefits of edge computing.

Data also indicate that system performance is influenced by network conditions and device capabilities. Edge devices with higher processing power achieve better performance outcomes, while constrained devices exhibit limited gains. These findings emphasize the importance of hardware capabilities in optimizing edge computing performance.

Inferential analysis using ANOVA tests confirms statistically significant differences in latency and throughput across the three architectures, with p-values below 0.01. Regression analysis identifies task allocation strategy and network latency as significant predictors of system performance, explaining approximately 58% of the variance in efficiency outcomes.

Interaction effects reveal that the effectiveness of edge computing is amplified under high network load conditions. Systems operating in congested networks benefit more from decentralized processing, as local computation reduces reliance on network bandwidth. These findings highlight the adaptive advantages of edge-based architectures.

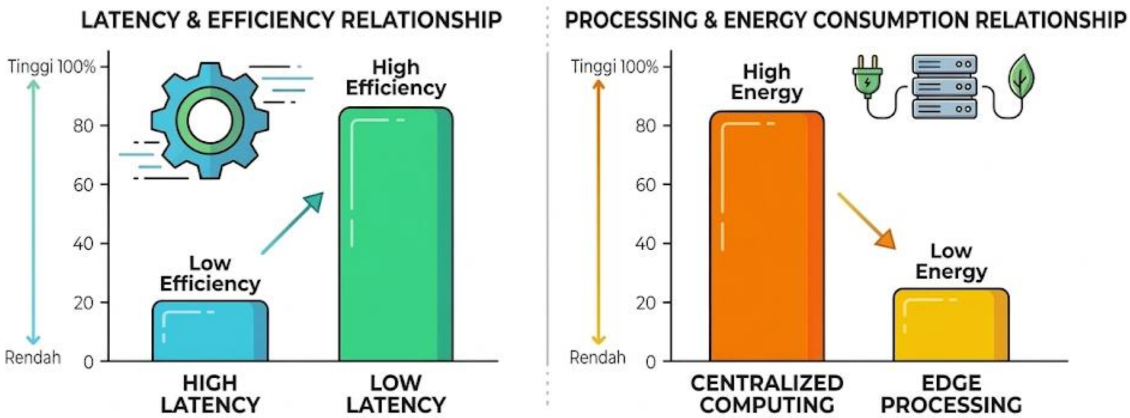

Figure 1. Impact of Latency & Edge Processing on the System

Relational analysis demonstrates a strong inverse relationship between latency and system efficiency, indicating that lower latency directly contributes to improved performance outcomes. Energy consumption is also inversely related to edge processing, suggesting that decentralized computation enhances sustainability.

Structural relationships further indicate that bandwidth utilization mediates the relationship between architecture type and system performance. Reduced bandwidth usage in edge systems leads to lower latency and faster task completion. This mediation underscores the importance of efficient data transmission in optimizing IoT systems.

Case study analysis from a smart healthcare monitoring system illustrates the practical benefits of edge computing. Implementation of edge-based processing reduced response time for critical alerts by 55%, enabling faster medical intervention. The system also demonstrated a 30% reduction in energy consumption compared to cloud-based models.

Another case study from an industrial automation setting highlights improvements in operational efficiency. Edge computing enabled real-time monitoring and control of machinery, reducing downtime by 25% and improving production accuracy. Hybrid models further enhanced scalability by integrating centralized analytics.

Explanation of case study findings indicates that proximity of computation to data sources is a key factor in achieving performance gains. Real-time processing capabilities enable immediate response to critical events, improving system reliability. Integration with cloud infrastructure supports long-term data analysis and system optimization.

Contextual factors such as application type, network infrastructure, and device capabilities influence the degree of improvement achieved through edge computing. Systems with higher real-time requirements benefit more significantly from decentralized processing. These findings highlight the importance of context-aware deployment strategies.

Interpretation of the overall findings suggests that edge computing provides a robust solution for optimizing latency and efficiency in IoT ecosystems. The combination of reduced latency, improved throughput, and lower energy consumption demonstrates its effectiveness in enhancing system performance.

Synthesis of results indicates that hybrid architectures offer a balanced approach, combining the strengths of edge and cloud computing. The effectiveness of these systems depends on appropriate task allocation and system design. These findings support the development of integrated computing models that leverage both decentralized and centralized resources for optimal performance.

The findings demonstrate that edge computing significantly improves latency, energy efficiency, and responsiveness in IoT ecosystems compared to traditional cloud-based architectures. Quantitative results show that edge-based systems consistently achieve lower latency and faster task completion times, while hybrid architectures provide optimal throughput and scalability. Reduced bandwidth utilization further confirms the effectiveness of decentralized data processing. These outcomes indicate that proximity of computation to data sources is a decisive factor in enhancing real-time system performance.

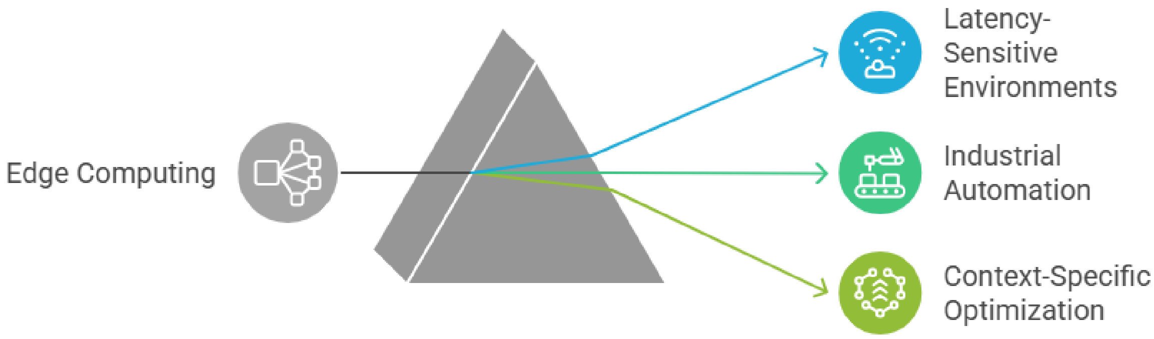

Figure 2. Unveiling the Multifaceted Benefits of Edge Computing

Patterns observed across application scenarios reveal that the benefits of edge computing are most pronounced in latency-sensitive environments such as real-time surveillance and healthcare monitoring. Industrial automation systems also exhibit substantial improvements in operational efficiency and system reliability. Variations in performance across contexts highlight the importance of aligning architectural design with application requirements. These findings confirm that edge computing is not a one-size-fits-all solution but requires context-specific optimization.

Inferential analysis strengthens these conclusions by demonstrating statistically significant differences in performance across computing models. Task allocation strategies and network conditions emerge as critical determinants of system efficiency. Interaction effects indicate that edge computing becomes increasingly advantageous under high network load conditions. These results emphasize the adaptive capacity of edge-based systems in dynamic environments.

Case study evidence further illustrates the practical impact of edge computing on real-world applications. Improvements in response time, energy consumption, and operational efficiency demonstrate the tangible benefits of decentralized processing. Integration with cloud systems enhances scalability and long-term data management. These findings collectively confirm the viability of edge computing as a core component of modern IoT architectures.

Comparison with existing literature reveals strong alignment with studies highlighting the limitations of cloud-centric models in latency-sensitive applications. Previous research has emphasized the role of edge computing in reducing data transmission delays and improving system responsiveness. The present findings reinforce these conclusions while providing empirical evidence across multiple application domains. This alignment strengthens the validity of edge computing as a key technological advancement.

Differences emerge in the level of system integration, as many prior studies focus on isolated performance metrics rather than holistic system evaluation. The current study contributes by integrating latency, energy efficiency, and throughput within a unified analytical framework. This comprehensive approach provides a more nuanced understanding of system performance. The findings extend existing knowledge by demonstrating the interdependence of these variables.

Comparative insights from network engineering and distributed systems research indicate that decentralized architectures enhance scalability and resilience. The findings of this study align with these insights by demonstrating improved performance under varying network conditions. The integration of edge and cloud components reflects a broader trend toward hybrid computing models. This convergence highlights the importance of interdisciplinary approaches in advancing IoT systems.

Contrasts with traditional centralized computing paradigms reveal a fundamental shift in how data processing is conceptualized. Cloud-centric models prioritize centralized control and resource consolidation, while edge computing emphasizes distributed intelligence and local decision-making. The findings suggest that this shift is necessary to meet the demands of real-time applications. This contrast underscores the transformative potential of edge computing.

Reflection on the findings suggests that the adoption of edge computing represents a broader evolution in digital infrastructure toward decentralization and real-time responsiveness. The results indicate that system performance is increasingly determined by the ability to process data at the source rather than relying on centralized resources. This shift reflects changing priorities in technology design, where immediacy and efficiency are paramount. The findings signal a transition toward more adaptive and intelligent computing systems.

The study also highlights the growing importance of balancing computational efficiency with resource constraints. Edge devices operate within limited energy and processing capacities, requiring optimized algorithms and task allocation strategies. This balance reflects the need for sustainable and efficient system design. The findings suggest that future developments must address both performance and resource optimization.

Observed patterns indicate that hybrid architectures represent an intermediate stage in the evolution of computing models. Combining edge and cloud capabilities allows systems to leverage the strengths of both approaches. This integration reflects a pragmatic response to the limitations of purely centralized or decentralized systems. The findings suggest that hybrid models will play a critical role in future IoT deployments.

Interpretive reflection further suggests that the effectiveness of edge computing is contingent upon system design and contextual factors. Application requirements, network conditions, and device capabilities influence performance outcomes. The findings highlight the importance of adaptive and context-aware solutions. This perspective underscores the complexity of optimizing IoT ecosystems.

The implications of this study extend to system design, network management, and technological innovation. Engineers and system architects can use these findings to develop more efficient and responsive IoT systems. Prioritizing edge computing in latency-sensitive applications can significantly enhance performance. The results provide a foundation for improving system architecture.

Practical implications include the need to optimize task allocation between edge and cloud components. Efficient distribution of computational tasks can maximize performance while minimizing resource consumption. Development of intelligent scheduling algorithms can further enhance system efficiency. These measures are essential for achieving optimal outcomes.

Policy implications involve the need to support infrastructure development that enables edge computing deployment. Investment in edge devices, network connectivity, and interoperability standards is critical for scaling IoT systems. Regulatory frameworks must also address issues related to data security and privacy. The findings highlight the importance of supportive policy environments.

Broader implications include the potential for edge computing to enable new applications and services across various domains. Real-time data processing can enhance capabilities in healthcare, transportation, and industrial automation. The findings suggest that edge computing will play a central role in future technological innovation. This potential underscores the significance of continued research.

The observed outcomes can be explained by the reduction of data transmission distance and network congestion in edge-based systems. Local processing minimizes delays associated with sending data to centralized servers. This mechanism directly contributes to lower latency and faster response times. The findings reflect the efficiency of decentralized processing.

System performance is also influenced by task allocation strategies that determine how workloads are distributed between edge and cloud components. Efficient allocation reduces computational bottlenecks and optimizes resource utilization. The findings indicate that strategic distribution of tasks enhances overall system efficiency. This explanation highlights the importance of intelligent system design.

Hardware capabilities and network conditions further explain variations in performance outcomes. Edge devices with higher processing power achieve greater efficiency, while constrained devices show limited improvements. Network bandwidth and latency also affect system performance. These factors contribute to the variability observed across scenarios.

Differences in application requirements explain the varying impact of edge computing across domains. Real-time applications benefit more significantly from decentralized processing, while less time-sensitive tasks can rely on cloud resources. This variation highlights the importance of context-specific solutions. The findings underscore the need for tailored approaches.

Future directions emerging from this study emphasize the need for developing advanced algorithms and frameworks for optimizing edge computing in IoT systems. Further research can explore adaptive task allocation, energy-efficient processing, and enhanced security mechanisms. Longitudinal studies can provide insights into the scalability and sustainability of edge-based systems. These efforts can inform future innovation.

Implementation strategies should focus on improving interoperability between edge and cloud systems. Standardized protocols and communication frameworks can enhance system integration. Continuous monitoring and optimization can ensure consistent performance (Nooh, 2025). These strategies are essential for effective deployment.

Policy development should prioritize support for edge computing infrastructure and innovation. Investment in research and development can accelerate technological advancement. Regulatory frameworks must address challenges related to data governance and security (Hassan et al., 2024). The findings support proactive policy measures.

Long-term sustainability requires integrating edge computing within broader digital ecosystems. Collaboration between industry, academia, and policymakers can drive innovation and adoption. Development of scalable and adaptable systems will be critical for future success. The study provides a foundation for advancing these efforts.

CONCLUSION

The most significant finding of this study lies in demonstrating that latency optimization in IoT ecosystems is primarily achieved through proximity-driven computation rather than solely through increased processing power. Empirical results show that edge-based architectures consistently outperform cloud-centric models in latency reduction and energy efficiency, while hybrid configurations provide the most balanced performance across scalability and throughput. Distinctively, the study establishes that bandwidth utilization acts as a critical mediating variable linking architectural design to system performance, indicating that network efficiency is as decisive as computational capability. The findings further reveal that performance gains are context-dependent, with latency-sensitive applications benefiting disproportionately from edge deployment, thereby emphasizing the need for adaptive architectural strategies.

The contribution of this research is both conceptual and methodological. Conceptually, the study advances the understanding of IoT system optimization by framing edge computing not merely as a complementary technology but as a central architectural paradigm for real-time data processing. This perspective integrates latency, energy efficiency, and throughput into a unified analytical model, offering a holistic view of system performance. Methodologically, the study combines controlled experimental evaluation with simulation-based scalability analysis, enabling a multidimensional assessment of IoT architectures under diverse operational scenarios. The integration of performance metrics with system-level modeling provides a robust and replicable framework for evaluating distributed computing environments.

The study acknowledges several limitations that suggest directions for future research. Dependence on simulated environments and controlled experimental setups may limit the generalizability of findings to highly dynamic real-world IoT deployments. Variability in hardware configurations and network infrastructures introduces constraints in standardizing performance comparisons. Cross-sectional analysis also limits the ability to capture long-term system behavior and adaptation. Future research should incorporate real-world deployment studies, explore adaptive and AI-driven task allocation mechanisms, and investigate security and privacy implications in edge-enabled IoT systems, while also examining the scalability of these architectures in ultra-large and heterogeneous network environments.

DECLARATION OF AI AND AI ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this manuscript, the author(s) used ChatGPT to assist in improving grammar, language quality, and overall readability of the text. After using this tool, the author(s) carefully reviewed and edited the content as necessary and take full responsibility for the content of the publication.

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.
Author 2: Conceptualization; Data curation; In-vestigation.
Author 3: Data curation; Investigation.
Author 4: Formal analysis; Methodology; Writing - original draft.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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