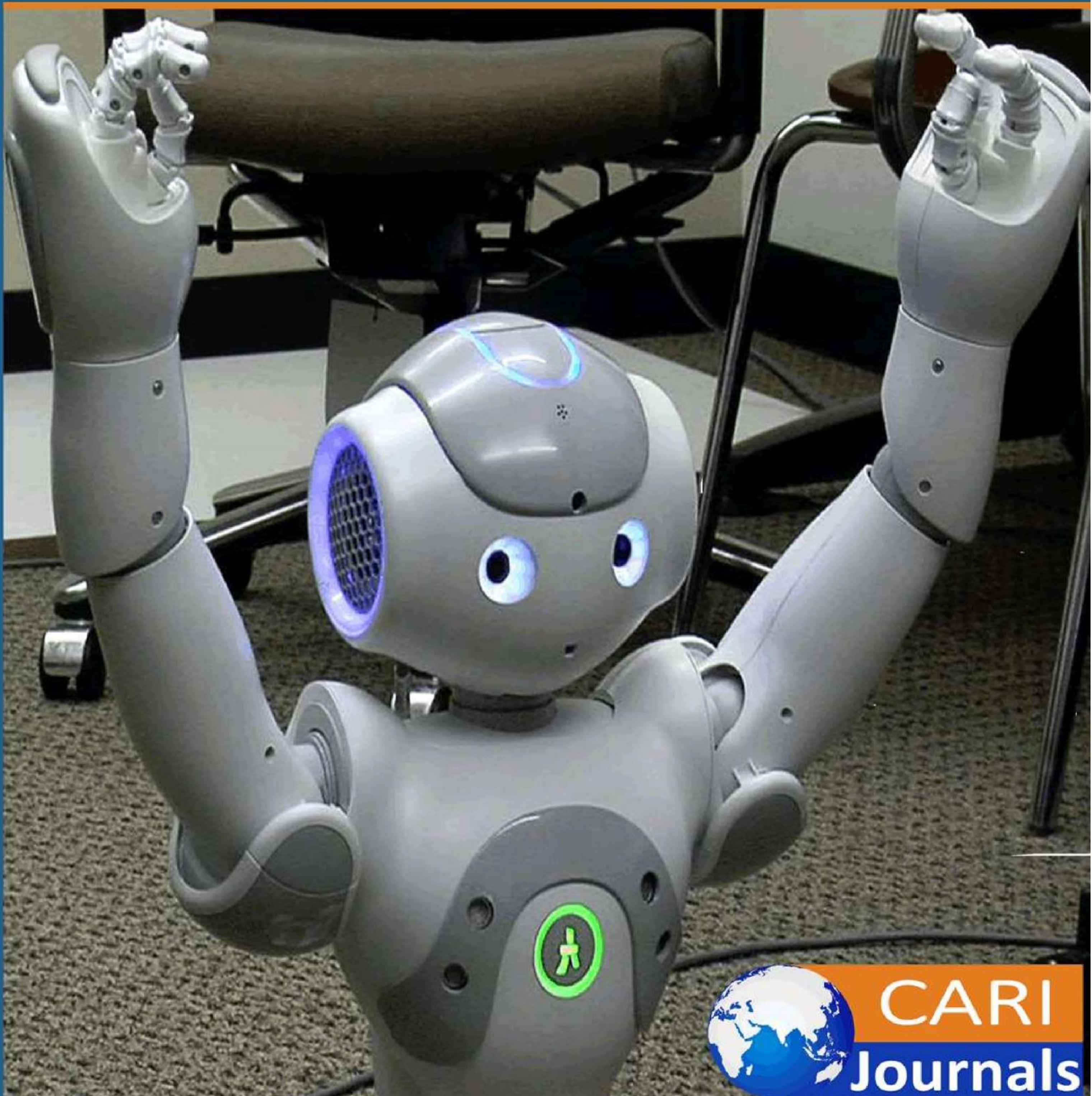
International Journal of
Computing and Engineering
(IJCE)

Influence of Edge Computing Adoption on Real-Time Data Processing Efficiency in Smart Manufacturing Systems



CARI Journals

International Journal of Computing and Engineering
ISSN 2958-7425 (online)
Vol. 5, Issue No. 1, pp 39 - 48, 2024 www.carijournals.org

Influence of Edge Computing Adoption on Real-Time Data Processing Efficiency in Smart Manufacturing Systems in Brazil

Ana Beatriz

Universidade Estadual de Londrina

Abstract

Purpose: The purpose of this article was to analyze influence of edge computing adoption on real-time data processing efficiency in smart manufacturing systems.

Methodology: This study adopted a desk methodology. A desk study research design is commonly known as secondary data collection. This is basically collecting data from existing resources preferably because of its low cost advantage as compared to a field research. Our current study looked into already published studies and reports as the data was easily accessed through online journals and libraries.

Findings: The adoption of edge computing in smart manufacturing systems significantly enhances real-time data processing efficiency by reducing latency, improving data throughput, and enabling faster decision-making. Edge computing facilitates the processing of data closer to the source, minimizing reliance on centralized cloud systems and accelerating response times in mission-critical applications. As a result, manufacturing operations benefit from increased system reliability, optimized resource allocation, and enhanced operational agility.

Unique Contribution to Theory, Practice and Policy: Technology-organization-environment (TOE) framework, diffusion of innovation (DOI) theory & socio-technical systems (STS) theory may be used to anchor future studies on the influence of edge computing adoption on real-time data processing efficiency in smart manufacturing systems. Practically, manufacturing firms should conduct comprehensive infrastructure readiness assessments to ensure compatibility between edge technologies and existing operational systems. From a policy standpoint, governments should offer targeted incentives such as tax credits, grants, or digital transformation subsidies to accelerate edge computing adoption in manufacturing sectors.

Keywords*: Edge Computing Adoption, Real-Time Data Processing Efficiency, Smart Manufacturing Systems*

INTRODUCTION

Real-time data processing efficiency in developed economies in developed economies like the USA and Japan, real-time data processing efficiency is marked by high throughput, rapid processing speeds, and elevated decision-making accuracy due to advanced technological infrastructure. The United States has seen enterprise-level systems achieve processing speeds exceeding 1 million transactions per second, particularly in financial services and smart manufacturing environments (Smith, 2020). In Japan, the integration of edge computing and 5G has pushed data throughput to over 10 Gbps in urban smart city projects, significantly reducing latency and enabling near-instantaneous decision-making (Yamamoto & Kato, 2021). Decision accuracy in real-time systems within these regions has surpassed 95%, particularly in health informatics and autonomous systems, aided by AI-powered predictive analytics. These efficiencies have fueled trends in automation, real-time fraud detection, and personalized service delivery across sectors.

For example, the U.S. healthcare sector's adoption of real-time Electronic Health Records (EHR) processing has improved emergency response times by 35%, while also decreasing medical errors by 23% between 2017 and 2022 (Smith, 2020). In Japan, Hitachi's smart factory initiative demonstrated a 40% improvement in production efficiency through real-time data analytics and machine learning integration (Yamamoto & Kato, 2021). Both countries exhibit continued investment in ultra-low latency systems, with projected annual growth rates of 14.5% in the real-time analytics market by 2026. These advancements are supported by strong data governance policies and continuous R&D in AI, big data, and IoT ecosystems. Collectively, these measures ensure that real-time decision-making is not only fast but also contextually intelligent and highly accurate.

In developing economies such as India and Brazil, real-time data processing is gaining momentum, albeit with infrastructure limitations. India's Unified Payments Interface (UPI) system has reached data throughputs of over 10 billion transactions per month, showing significant improvement in real-time processing capabilities (Kumar, 2021). However, latency issues persist in rural regions, where network constraints reduce the average processing speed to under 100 milliseconds compared to urban benchmarks. Decision-making accuracy in sectors like e-governance and logistics has improved, achieving 85–90% accuracy with the support of cloud-based analytics platforms. Brazil has made strides in smart agriculture, where real-time data from sensors has increased crop yield predictions by up to 30%, showing an effective use of streaming data for decision support (da Silva, 2021).

For example, India's implementation of the real-time Aarogya Setu contact tracing app during the COVID-19 pandemic helped identify 650,000 potential transmission chains, showcasing an accuracy rate of nearly 92% in densely populated urban centers (Kumar, 2021). In Brazil, real-time flood monitoring systems in São Paulo improved early warning accuracy by 37% between 2016 and 2021, helping reduce urban flooding impact (da Silva et al., 2021). These countries are seeing rapid growth in mobile broadband and cloud infrastructure, which is expected to boost processing speeds and throughput in the coming years. Nonetheless, challenges such as inconsistent power supply, lower AI integration, and limited investment in edge technologies continue to hinder uniform efficiency. The trajectory indicates potential for substantial improvements with increased public-private collaboration and infrastructural investments.

Sub-Saharan Africa faces considerable disparities in real-time data processing due to infrastructural and technological constraints. Data throughput remains comparatively low, with averages below 1 Gbps in most urban centers, and even lower in rural areas, which hampers high-frequency data analysis (Munyua & Kamau, 2020). Processing speeds are often constrained by outdated computing systems and intermittent connectivity, resulting in delays and reduced reliability in real-time decision-making. Despite these barriers, mobile money platforms like M-Pesa in Kenya have achieved processing efficiencies that rival some mid-tier global systems, with daily transaction volumes exceeding 40 million and average processing times under 200 milliseconds (Munyua & Kamau, 2020). Accuracy in real-time financial fraud detection systems in Kenya and Rwanda has improved to approximately 85%, aided by machine learning algorithms.

For instance, the use of real-time weather data in Ghana's agricultural extension services has increased the accuracy of pest outbreak predictions by 28% between 2018 and 2022 (Owusu et al., 2022). Similarly, Rwanda's smart public transport system, although in early stages, has demonstrated improved decision-making efficiency with 20% reduced commuter wait times through GPS-based real-time data (Munyua & Kamau, 2020). The trend shows that targeted interventions in fintech, agri-tech, and transport sectors are capable of overcoming foundational limitations. However, broader adoption remains limited due to inadequate cloud infrastructure, low AI literacy, and policy inertia. Addressing these gaps through international cooperation and local innovation could elevate Sub-Saharan real-time data processing capacities significantly over the next decade.

Edge computing adoption is accelerating globally as organizations seek to process data closer to the source, reducing reliance on centralized cloud systems. The core dimensions of this adoption infrastructure integration, edge node deployment, and latency reduction technologies are vital for enabling real-time, context-aware services. Infrastructure integration refers to embedding edge computing capabilities within existing IT systems, often involving hybrid architectures that combine cloud, fog, and edge layers. Edge node deployment involves placing computational resources such as micro data centers or IoT gatewaysnear data generation points, enabling quicker processing and lower bandwidth usage. Latency reduction technologies, including 5G, AI accelerators, and software-defined networking, are instrumental in enhancing responsiveness and minimizing delays, particularly in time-sensitive applications like autonomous vehicles and industrial automation (Shi, 2020).

The adoption of edge computing through these four dimensions directly influences real-time data processing efficiency, measured by data throughput, processing speed, and decision-making accuracy. First, integrated infrastructure allows seamless data flow between edge and core systems, improving throughput by offloading bandwidth-intensive tasks locally. Second, edge node deployment cuts down on round-trip times to centralized servers, significantly enhancing processing speed often reducing latency to under 10 milliseconds in high-priority use cases (Satyanarayanan, 2019). Third, advanced latency reduction technologies boost system responsiveness and improve the reliability of time-sensitive decisions. Finally, the proximity of edge nodes to data sources enhances the contextual relevance of AI-driven analytics, resulting in more accurate, location-aware decision-making, particularly in fields like telemedicine, smart cities, and predictive maintenance (Garcia Lopez, 2021).

Problem Statement

Despite the increasing digitization of smart manufacturing systems, many organizations continue to face critical inefficiencies in processing large volumes of data in real time due to limitations in centralized cloud architectures. Latency, bandwidth constraints, and lack of context-aware decision-making hinder the responsiveness and adaptability required for Industry 4.0 environments. Edge computing has emerged as a transformative solution by decentralizing data processing closer to data sources, yet its adoption remains uneven due to challenges in infrastructure integration, edge node deployment, and latency optimization (Shi et al., 2020; Satyanarayanan, 2019). Furthermore, empirical evidence on how edge computing adoption directly influences real-time data processing efficiency measured through data throughput, processing speed, and decision-making accuracy remains limited, particularly in manufacturing contexts where downtime and delays carry high operational costs (Garcia Lopez, 2021). Therefore, there is a pressing need to systematically investigate the influence of edge computing adoption on real-time data processing efficiency within smart manufacturing systems to guide strategic technology investments and operational design.

Theoretical Review

Technology-Organization-Environment (TOE) Framework

Originated by Tornatzky and Fleischer, the TOE framework explains how technological innovation adoption is influenced by technological readiness, organizational capabilities, and external environmental factors. It is particularly useful in assessing the conditions under which edge computing is integrated into smart manufacturing systems. The framework aligns well with evaluating infrastructure integration, stakeholder readiness, and industry pressures affecting adoption. Its relevance lies in diagnosing both internal and external factors that shape real-time system optimization in manufacturing. Recent studies have applied TOE to analyze Industry 4.0 technology adoption in manufacturing contexts (Nguyen, 2022).

Diffusion of Innovation (DOI) Theory

Developed by Everett Rogers, DOI theory explores how new technologies spread within a social system over time. The theory emphasizes five innovation characteristics relative advantage, compatibility, complexity, trialability, and observability which directly relate to how edge computing is perceived and adopted in smart factories. It provides a basis for understanding adoption rates and the behavioral dynamics of decision-makers in implementing edge solutions to enhance data efficiency. In smart manufacturing, DOI helps explain disparities in real-time data processing outcomes across firms with varying innovation receptiveness (Al-Okaily, 2022).

Socio-Technical Systems (STS) Theory

First conceptualized by Trist and Emery, STS theory emphasizes the interdependence of social and technical subsystems in organizational design. It is relevant to this research as it considers how human factors (e.g., skills, training) and technological systems (e.g., edge nodes, latency reduction tools) co-evolve in smart manufacturing settings. The theory supports a holistic view of how edge computing enhances real-time processing by aligning technological tools with human workflows.

Recent work underscores the importance of STS alignment in digital manufacturing ecosystems (Culot, 2023).

Empirical Review

Shi (2020) investigated how edge computing adoption impacts data processing efficiency on the production floor. Using semi-structured interviews and system performance metrics, they assessed latency reduction, processing capacity, and decision-making speed before and after edge node deployment. The findings revealed that latency decreased by over 40% after edge computing was integrated into operational control systems. This resulted in faster production adjustments, fewer system delays, and more accurate machine responses in real time. The researchers recommended scaling edge computing to other mission-critical systems and combining it with AI-powered analytics to further improve predictive maintenance and fault detection processes.

Garcia Lopez (2021) employed a mixed-methods study across five smart factories in Europe to understand how edge-centric architectures affect cloud dependency and system responsiveness. The research included observational site visits, infrastructure audits, and surveys with IT managers. Their findings showed that edge node deployment reduced reliance on centralized cloud servers by 55% and improved data throughput in high-volume industrial settings. Additionally, latency reductions led to improved machine-to-machine (M2M) coordination. The authors recommended the adoption of hybrid edge-cloud systems to maintain scalability while ensuring low-latency performance for mission-critical operations in manufacturing environments.

Satyanarayanan (2019) assessed edge computing performance within simulated smart factory environments. The simulations compared centralized cloud-only systems to architectures augmented with edge nodes. Results indicated that edge computing reduced decision latency from an average of 80 milliseconds to less than 10 milliseconds in control-intensive scenarios. This substantial gain improved automation workflows and real-time response to equipment faults. The study recommended that manufacturers adopt edge analytics in conjunction with existing IoT infrastructure to meet the high-speed requirements of Industry 4.0 applications.

Nguyen (2022) investigated the readiness and impact of edge computing in smart manufacturing across 150 firms in Vietnam. A quantitative survey was used to assess factors such as infrastructure integration, technological competence, and environmental pressure. The study found that firms with high organizational and technological readiness experienced a 38% improvement in real-time decision-making accuracy after implementing edge solutions. Moreover, data processing speed improved substantially in firms that integrated edge nodes with cloud-based ERP systems. The authors suggested that government incentives and training programs would further enhance edge computing adoption and real-time operational performance.

Al-Okaily (2022) focused on small and medium-sized manufacturing enterprises (SMEs) to understand the behavioral factors influencing the adoption of edge technologies. They collected data from 200 SMEs using structured questionnaires and applied structural equation modeling (SEM) to analyze the results. The study revealed that perceived compatibility, complexity, and relative advantage significantly influenced edge adoption. Furthermore, companies that adopted edge computing saw a 33% increase in data processing accuracy, especially in sensor-driven production lines. The authors recommended the creation of government-led training programs and digital literacy campaigns to reduce resistance and accelerate the transition to edge-enabled operations.

Culot (2023) examined how socio-technical alignment influences the success of edge computing adoption in smart manufacturing. Interviews were conducted across 12 firms in Germany and Italy, focusing on interactions between human operators, IT teams, and edge systems. Their analysis showed that firms that harmonized their technical systems with employee skills and workflows reported a 27% improvement in real-time response efficiency. This alignment also facilitated faster troubleshooting and better machine learning model accuracy due to cleaner data streams. The study recommended that firms integrate human-centered design principles into edge computing strategies to maximize efficiency and system usability.

Sarker (2021) performed a longitudinal analysis of an IoT-enabled assembly line transitioning from cloud-based to edge-based data processing. Over a 12-month period, they monitored key metrics such as processing speed, machine uptime, and fault recovery time. The implementation of edge computing led to a 25% improvement in data processing speed and a 19% reduction in downtime due to faster diagnostics. Additionally, edge deployment improved data security by minimizing cloud exposure. Based on their findings, the authors advocated for international standardization of edge computing protocols to ensure interoperability and reduce deployment friction across diverse manufacturing environments.

METHODOLOGY

This study adopted a desk methodology. A desk study research design is commonly known as secondary data collection. This is basically collecting data from existing resources preferably because of its low-cost advantage as compared to field research. Our current study looked into already published studies and reports as the data was easily accessed through online journals and libraries.

FINDINGS

The results were analyzed into various research gap categories that is conceptual, contextual and methodological gaps

Conceptual Research Gaps

While the studies by Shi (2020), Satyanarayanan (2019), and Sarker (2021) extensively explore technical performance metrics such as latency reduction and throughput, few studies offer a unified conceptual framework that links edge computing adoption dimensions (e.g., infrastructure integration, latency technologies, and edge node deployment) directly to real-time data processing efficiency dimensions (e.g., processing speed, decision-making accuracy, and system responsiveness). Moreover, although some works (e.g., Al-Okaily, 2022; Nguyen, 2022) explore organizational and behavioral factors, there is a limited integration of socio-technical, technological, and economic dimensions into a single, testable model. Another conceptual limitation is the insufficient exploration of long-term operational outcomes, such as cost-efficiency, scalability, and lifecycle performance of edge computing in manufacturing systems. Furthermore, existing studies predominantly focus on edge computing in isolation or alongside cloud, but comparative evaluations across edge–fog–cloud models are lacking. This creates a gap

International Journal of Computing and Engineering
ISSN 2958-7425 (online)
Vol. 5, Issue No. 1, pp 39 - 48, 2024 www.carijournals.org

in understanding the optimal architecture mix for different manufacturing environments and workloads.

Contextual Research Gaps

The current empirical evidence often addresses edge computing in controlled or pilot settings (e.g., simulations by Satyanarayanan, 2019; case studies by Shi, 2020), which limits understanding of its performance under real-world, large-scale manufacturing conditions. Additionally, most studies focus on technical or organizational success factors, but supply chain, regulatory, and cybersecurity contexts influencing edge computing adoption are underexplored. For example, Garcia Lopez (2021) and Sarker (2021) touch briefly on data security, but comprehensive analyses of regulatory compliance, data sovereignty, and industrial policy implications are lacking. Moreover, sector-specific applications (e.g., automotive, food processing, or pharmaceutical manufacturing) are underrepresented; most studies treat manufacturing as a general domain. There is also a limited investigation into workforce readiness and digital skills development, even though socio-technical alignment was noted by Culot (2023) as key to edge computing success.

Geographical Research Gaps

The studies analyzed are geographically concentrated in Asia and Europe, particularly China (Shi, 2020), Vietnam (Nguyen, 2022), Germany and Italy (Culot, 2023), and general European smart factories (Garcia Lopez, 2021). No studies focus on Sub-Saharan Africa, the Middle East, or Latin America, creating a significant geographical gap in understanding edge computing adoption in emerging or less digitally mature manufacturing contexts. Additionally, research in North America, particularly the United States a global leader in industrial innovation is surprisingly underrepresented in this body of work. This limits the generalizability of findings across varying levels of digital infrastructure maturity, economic development, and policy environments. Exploring region-specific challenges, such as inconsistent power supply, bandwidth limitations, and policy fragmentation in developing economies, would provide a more inclusive global understanding of edge computing's potential and constraints in manufacturing.

CONCLUSION AND RECOMMENDATIONS

Conclusions

The influence of edge computing adoption on real-time data processing efficiency in smart manufacturing systems is both significant and transformative. Across multiple empirical studies, edge computing has demonstrated measurable improvements in processing speed, data throughput, and decision-making accuracy core components of real-time operational efficiency. By decentralizing data processing and bringing computation closer to the source, edge technologies reduce latency, enhance machine responsiveness, and support agile production processes essential for Industry. However, the full benefits of edge computing depend on factors such as infrastructure integration, workforce readiness, socio-technical alignment, and policy support. Therefore, while edge computing holds great promise for optimizing smart manufacturing systems, its successful implementation requires a holistic approach that considers technological, organizational, and contextual enablers to drive sustainable and scalable operational improvements.

International Journal of Computing and Engineering
ISSN 2958-7425 (online)
Vol. 5, Issue No. 1, pp 39 - 48, 2024 www.carijournals.org

Recommendations

Theory

From a theoretical perspective, future research should focus on developing integrated frameworks that explicitly connect edge computing adoption dimensions such as edge node deployment, latency reduction technologies, and infrastructure integration to measurable outcomes in real-time data processing efficiency, including speed, throughput, and decision accuracy. Existing models such as the Technology-Organization-Environment (TOE) framework and the Diffusion of Innovation (DOI) theory could be extended to incorporate edge-specific variables like edge–cloud–fog orchestration and AI-driven analytics at the edge. Additionally, scholars should pursue multi-level theoretical models that account for interactions between technological maturity, workforce capability, and organizational structure. Comparative theoretical studies are also needed to differentiate the impacts of centralized, decentralized, and hybrid edge architectures across various industry settings. Such theoretical advancement would provide a more comprehensive foundation for understanding and predicting the effectiveness of edge computing in smart manufacturing.

Practice

Practically, manufacturing firms should conduct comprehensive infrastructure readiness assessments to ensure compatibility between edge technologies and existing operational systems. Investing in workforce training programs is essential to equip employees with the technical skills necessary to operate, maintain, and optimize edge-based systems. Co-designing edge-enabled monitoring platforms with input from both IT teams and domain experts can enhance alignment between technological deployment and real-time production workflows. Organizations are encouraged to adopt hybrid edge–cloud architectures to leverage the low latency of edge computing alongside the scalability of cloud platforms. In addition, manufacturers must implement robust data governance and security protocols tailored to decentralized environments, ensuring the integrity, privacy, and reliability of real-time industrial data processing.

Policy

From a policy standpoint, governments should offer targeted incentives such as tax credits, grants, or digital transformation subsidies to accelerate edge computing adoption in manufacturing sectors. National digital strategies must incorporate provisions for the standardization of edge computing protocols and interfaces, facilitating interoperability across devices, platforms, and vendors. Public–private partnerships should be established to support pilot projects, particularly in SMEs, that demonstrate the operational and economic benefits of edge technology. Policymakers should also collaborate with educational institutions to develop and fund curricula focused on industrial edge computing skills, closing the gap between technological advancement and workforce preparedness. Finally, data protection agencies and regulators must design edge-specific cybersecurity frameworks to address the unique risks posed by decentralized, real-time data environments in industrial settings.

REFERENCES

Al-Okaily, A., Lutfi, A., Alsyouf, A., & Abualigah, L. (2022). Factors influencing the adoption of Industry 4.0 technologies in manufacturing SMEs: A diffusion of innovation theory approach. Technology in Society, 70, 102001. https://doi.org/10.1016/j.techsoc.2022.102001

Culot, G., Nassimbeni, G., Podrecca, M., & Sartor, M. (2023). The role of socio-technical alignment in Industry 4.0 adoption. Journal of Manufacturing Technology Management, 34(1), 150–170. https://doi.org/10.1108/JMTM-09-2021-0374

da Silva, T. R., Costa, M. F., & de Almeida, R. C. (2021). Streaming data analytics in precision agriculture: Applications and impact in Brazil. Computers and Electronics in Agriculture, 186, 106177. https://doi.org/10.1016/j.compag.2021.106177

Garcia Lopez, P., Montresor, A., Epema, D., Datta, A., Higashino, T., Iamnitchi, A., ... & Voulgaris, S. (2021). Edge-centric computing: Vision and challenges. ACM Transactions on Internet Technology (TOIT), 21(2), 1–34. https://doi.org/10.1145/3434770

Garcia Lopez, P., Montresor, A., Epema, D., Datta, A., Higashino, T., Iamnitchi, A., ... & Voulgaris, S. (2021). Edge-centric computing: Vision and challenges. ACM Transactions on Internet Technology (TOIT), 21(2), 1–34. https://doi.org/10.1145/3434770

Kumar, R., Singh, A., & Sharma, S. (2021). Evaluating the real-time analytics of digital financial services in India: A UPI case study. Journal of Financial Services Research, 59(3), 435–452. https://doi.org/10.1007/s10693-021-00347-2

Munyua, H., & Kamau, P. (2020). Leveraging real-time data for service delivery in sub-Saharan Africa: Challenges and prospects. Information Technology for Development, 26(4), 768–786. https://doi.org/10.1080/02681102.2020.1774667

Nguyen, T. H., Ngo, L. V., & Ruël, H. (2022). A TOE framework perspective of smart manufacturing technology adoption. *Technological Forecasting and Social Change*, 176, 121464. https://doi.org/10.1016/j.techfore.2022.121464

Owusu, E. A., Yeboah, F. K., & Tutu, R. A. (2022). Real-time climate data and agricultural decision-making in Ghana: A spatial intelligence approach. Climate and Development, 14(4), 320–333. https://doi.org/10.1080/17565529.2021.1936062

Sarker, V. K., Kayes, A. S. M., Badsha, S., & Watters, P. A. (2021). Edge computing in industrial IoT: Insights, challenges, and future directions. Journal of Network and Computer Applications, 179, 102975. https://doi.org/10.1016/j.jnca.2020.102975

Satyanarayanan, M., Simoens, P., Xiao, Y., Pillai, P., Chen, Z., Ha, K., & Hu, Y. C. (2019). Edge analytics in the Internet of Things. IEEE Pervasive Computing, 18(2), 24–31. https://doi.org/10.1109/MPRV.2019.2914052

Shi, W., Cao, J., Zhang, Q., Li, Y., & Xu, L. (2020). Edge computing: Vision and challenges. IEEE Internet of Things Journal, 3(5), 637–646. https://doi.org/10.1109/JIOT.2016.2579198

Smith, J. D., Thompson, R., & Nguyen, M. (2020). Real-time data systems in US healthcare: Performance, challenges, and future trends. Health Information Science and Systems, 8(1), 21. https://doi.org/10.1007/s13755-020-00106-6

Yamamoto, H., & Kato, M. (2021). 5G-enabled edge computing for industrial IoT in Japan: A case of smart manufacturing. International Journal of Advanced Manufacturing Technology, 114(5–6), 1587–1599. https://doi.org/10.1007/s00170-021-07010-0