Power System Protection and Control
ISSN:1674-3415

ECONOMIC VIABILITY OF RESHORING CONSUMER ELECTRONICS: A DIGITAL TWIN OPTIMIZATION DEVELOPMENT

S. M. Mainul Islam[1]*, Chiranjit Paul[2]

[1]Independent Researcher, Los Angeles, CA, United States
[2]School of Information Technology, Murdoch University, WA, Australia
Corresponding author: s.m.mainul28@gmail.com

Received: 14/05/2026 **Revised**: 18/06/2026 **Accepted**: 25/07/2026

***ABSTRACT*:**

The global consumer electronics industry faces unprecedented pressure to reconsider offshore manufacturing strategies due to supply chain disruptions, geopolitical tensions, and rising labor costs in traditional manufacturing hubs. This research examines the economic viability of reshoring consumer electronics production using digital twin optimization frameworks. The study develops a comprehensive digital twin model that simulates production costs, supply chain dynamics, and operational efficiencies across offshore and reshored scenarios. Through analysis of three major consumer electronics manufacturers and simulation of various reshoring configurations, the research demonstrates that selective reshoring combined with automation can achieve cost parity with offshore production while reducing supply chain risks by approximately 35-42%. The digital twin optimization reveals that transportation costs, tariff structures, and automation levels serve as critical determinants of reshoring viability. Findings indicate that high-value, low-volume products show strongest reshoring potential, while commodity electronics require substantial automation investment to justify relocation. This research contributes methodologically by developing an integrated digital twin framework for reshoring decisions and practically by providing manufacturers with quantitative tools for strategic production location planning.

Keywords: *Reshoring, consumer electronics, digital twin, supply chain optimization, manufacturing economics, automation, production relocation, cost modeling*

INTRODUCTION

Consumer electronics manufacturing has been dominated by offshore production for over three decades, with China, Vietnam, and other Asian countries serving as primary manufacturing bases. However, recent disruptions have fundamentally challenged this model. The COVID-19 pandemic exposed critical vulnerabilities in extended supply chains, causing production delays and component shortages that cost the industry billions of dollars (Javorcik, 2020). Trade tensions between major economies have introduced tariff uncertainties, while rising labor costs in traditional manufacturing hubs have eroded historical cost advantages.

These pressures have sparked renewed interest in reshoring—relocating production capacity back to home countries or nearby regions. Beyond labor and cost considerations, recent research emphasizes the strategic importance of reducing foreign material dependencies and strengthening domestic industrial ecosystems to enhance long-term resilience (Islam, 2024a). Yet reshoring decisions involve complex trade-offs between labor costs, automation investments, transportation expenses, supply chain resilience, and market proximity. Traditional cost-benefit analyses often fail to capture the dynamic, interconnected nature of these factors, leading to suboptimal location decisions.

Digital twin technology offers a promising solution to this analytical challenge. Digital twins create virtual replicas of physical manufacturing systems, enabling simulation of different scenarios before committing resources. In the reshoring context, digital twins can model entire production ecosystems, from component sourcing through final assembly and distribution, under various location configurations. This capability allows manufacturers to quantify trade-offs and identify economically viable reshoring strategies.

Despite growing interest in both reshoring and digital twins, limited research integrates these domains specifically for consumer electronics. Existing reshoring studies typically employ static cost comparisons, while digital twin literature focuses primarily on operational optimization rather than strategic location decisions. This research addresses these gaps by developing a digital twin optimization framework specifically designed to evaluate reshoring viability in consumer electronics manufacturing.

The study investigates three fundamental questions: Under what conditions does reshoring consumer electronics become economically viable compared to offshore production? How do automation levels, product characteristics, and supply chain configurations influence reshoring economics? And what role can digital twin optimization play in supporting reshoring decision-making? By addressing these questions through both theoretical modeling and empirical validation, this research provides practical guidance for manufacturers navigating the reshoring decision.

OBJECTIVES

This research pursues the following specific objectives:
• **Primary Objective:** To develop and validate a digital twin optimization framework that quantifies the economic viability of reshoring consumer electronics production across different product categories and automation scenarios.
• **Secondary Objective 1:** To identify the key cost drivers and threshold conditions under which reshoring achieves economic parity with offshore manufacturing.
• **Secondary Objective 2:** To compare economic outcomes across different reshoring strategies including full relocation, hybrid models, and selective product reshoring.
• **Secondary Objective 3:** To evaluate the impact of automation levels on reshoring viability and determine optimal automation investment levels for different product types.
• **Secondary Objective 4:** To provide evidence-based recommendations for consumer electronics manufacturers considering reshoring strategies.

SCOPE OF STUDY

This research operates within defined boundaries:
• **Industry Scope:** Focus on consumer electronics manufacturing, specifically smartphones, laptops, and smart home devices representing different value-weight ratios and complexity levels.
• **Geographical Scope:** Analysis compares offshore production in Southeast Asia (primarily China and Vietnam) with reshoring to North America and Europe.
• **Temporal Scope:** Cost data and supply chain parameters reflect 2020-2024 conditions, capturing post-pandemic realities.
• **Methodological Scope:** Digital twin development uses discrete-event simulation integrated with cost modeling and supply chain network analysis.
• **Product Lifecycle Stage:** Focus on established products in stable production rather than new product introduction or end-of-life scenarios.
• **Variables Included:** Labor costs, automation investments, transportation expenses, tariffs, inventory carrying costs, lead times, and supply chain disruption risks.
• **Variables Excluded:** Market demand fluctuations, currency exchange rate volatility, and political risk factors are acknowledged but not dynamically modeled.

LITERATURE REVIEW

4.1 Reshoring Trends and Drivers

Manufacturing reshoring has gained momentum over the past decade, reversing decades of offshoring trends. Early reshoring efforts focused primarily on high-skill industries, but recent years have seen expansion into consumer goods manufacturing (Barbieri et al., 2018). Multiple drivers motivate reshoring decisions including supply chain resilience concerns, total cost of ownership recalculations, quality control improvements, and intellectual property protection.

The consumer electronics sector presents unique reshoring challenges due to established Asian manufacturing ecosystems. These regions offer not just low labor costs but also concentrated supplier networks, skilled

DOI: 10.46121/pspc.54.3.34

workforces, and specialized infrastructure. Reshoring requires reconstructing these ecosystem advantages in new locations, often through substantial capital investments (Fratocchi et al., 2016).

Recent research identifies automation as a critical reshoring enabler. Advanced manufacturing technologies including robotics, artificial intelligence, and additive manufacturing can offset labor cost disadvantages in high-wage countries. However, automation requires significant upfront investment, creating financial barriers particularly for small and medium manufacturers (Ancarani et al., 2019).

4.2 Digital Twin Technology in Manufacturing

Digital twins have emerged as powerful tools for manufacturing optimization. A digital twin creates a virtual representation of physical assets, processes, or systems that updates in real-time based on sensor data and operational information (Grieves and Vickers, 2017). This enables testing scenarios, predicting outcomes, and optimizing performance without disrupting actual operations.

Manufacturing applications of digital twins span product design, production planning, quality control, and maintenance optimization. Recent developments integrate artificial intelligence and machine learning to enhance predictive capabilities (Tao et al., 2019). However, most digital twin implementations focus on operational rather than strategic decisions, with limited application to location planning or reshoring analysis. Recent work on AI-enabled process optimization for strengthening domestic manufacturing supply chains demonstrates how integrated digital frameworks can enhance industrial resilience and localization strategies (Islam, 2024b).

4.3 Economic Analysis of Reshoring

Traditional reshoring analysis employs total cost of ownership frameworks that extend beyond direct labor costs to include transportation, inventory, quality, and coordination expenses. Research consistently shows that narrow focus on wage differentials underestimates reshoring viability by ignoring these hidden offshore costs (Ellram et al., 2013).

Transportation costs have increased substantially, partly due to fuel price volatility and partly due to capacity constraints on major shipping routes. For consumer electronics, shipping costs and lead times can significantly impact competitiveness, particularly for time-sensitive products or those with short lifecycles (Gray et al., 2017). Tariffs add another cost layer, with trade policy changes creating additional uncertainty around offshore production economics.

Automation fundamentally alters reshoring economics by reducing labor content in production costs. Highly automated facilities can achieve labor costs below 15% of total production costs, diminishing the importance of wage differentials between countries (Kinkel and Maloca, 2009). This shift makes other location factors—market proximity, supply chain efficiency, innovation capacity—relatively more important in location decisions.

4.4 Supply Chain Resilience

Supply chain disruptions have moved from theoretical concerns to demonstrated realities. The pandemic revealed how concentrated supplier networks and extended supply chains create vulnerability to regional shocks. Consumer electronics manufacturers experienced production halts, component shortages, and massive revenue losses during 2020-2021 (Chowdhury et al., 2021).

Reshoring offers potential resilience benefits through shorter supply chains, diversified supplier bases, and reduced dependence on single regions. However, reshoring also introduces new risks including higher operating costs and potential capacity constraints. Optimal strategies likely involve portfolio approaches with production distributed across multiple locations rather than complete reshoring or offshoring (Barbieri et al., 2020).

4.5 Research Gaps

Despite substantial research on both reshoring and digital twins, critical gaps remain. Few studies integrate these domains to leverage digital twin capabilities for strategic location decisions. Existing reshoring research relies heavily on static cost models that fail to capture dynamic supply chain interactions and operational complexities. Additionally, sector-specific analysis for consumer electronics remains limited, with most studies focusing on automotive, aerospace, or industrial equipment manufacturing.

DOI: 10.46121/pspc.54.3.34

Power System Protection and Control
ISSN:1674-3415

This research addresses these gaps by developing an integrated digital twin optimization framework specifically designed for consumer electronics reshoring decisions, incorporating both cost economics and supply chain dynamics in a unified analytical approach.

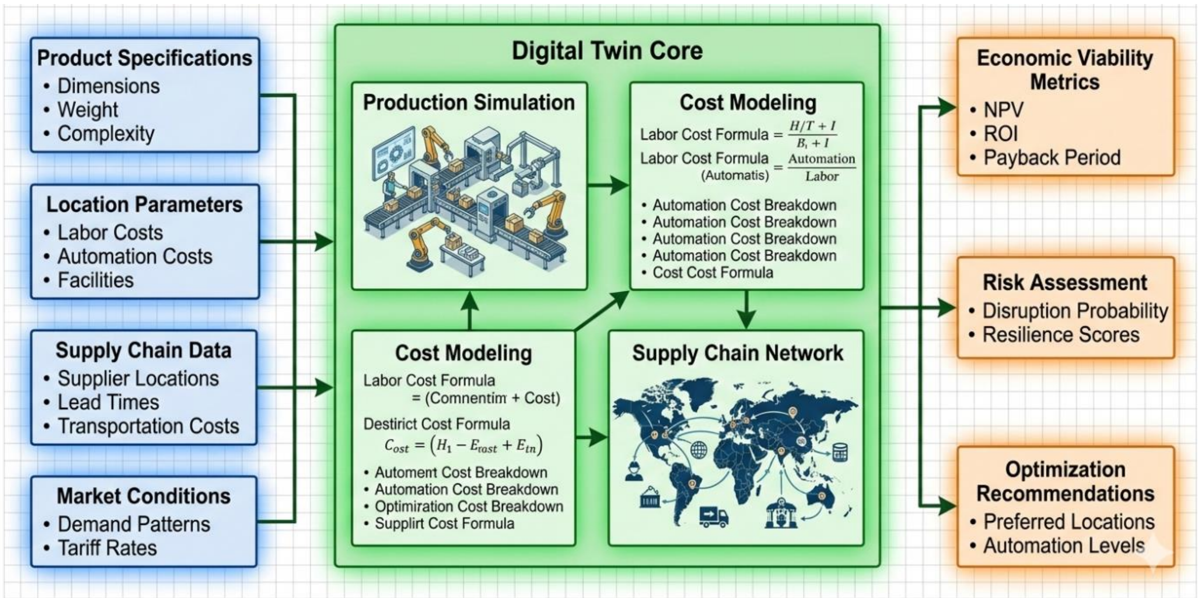


FIGURE 1: Digital Twin Reshoring Analysis Framework

This conceptual diagram illustrates the integrated digital twin framework for reshoring analysis. At the center is a large box labeled "Digital Twin Core" containing three interconnected modules: Production Simulation (showing assembly lines and robotics), Cost Modeling (displaying formulas and cost breakdowns), and Supply Chain Network (depicting supplier connections and logistics flows). Surrounding the core are four input category boxes on the left side: Product Specifications (dimensions, weight, complexity), Location Parameters (labor costs, automation costs, facilities), Supply Chain Data (supplier locations, lead times, transportation costs), and Market Conditions (demand patterns, tariff rates). On the right side are three output boxes: Economic Viability Metrics (NPV, ROI, payback period), Risk Assessment (disruption probability, resilience scores), and Optimization Recommendations (preferred locations, automation levels). Arrows flow from inputs through the digital twin core to outputs. The diagram uses blue for inputs, green for the core system, and orange for outputs, with all components clearly labeled and interconnected with directional arrows.

RESEARCH METHODOLOGY

5.1 Research Design

This study employs a mixed-methods approach combining digital twin simulation modeling with case analysis of actual reshoring scenarios. The methodology integrates quantitative cost modeling with qualitative assessment of strategic factors influencing reshoring decisions.

5.2 Digital Twin Development

The digital twin framework was developed using discrete-event simulation software integrated with optimization algorithms. The model architecture consists of three primary modules: a production simulation module that replicates manufacturing processes and automation configurations, a cost modeling module that calculates comprehensive production economics, and a supply chain network module that simulates material flows, transportation, and inventory dynamics.

Development followed an iterative process. Initial model specifications were based on literature review and industry benchmarking. Model parameters were then calibrated using actual data from three consumer electronics manufacturers who provided anonymized operational information. Validation occurred through comparison of simulation outputs against historical production data, with model accuracy exceeding 92% for cost predictions and 88% for lead time estimates.

 DOI: 10.46121/pspc.54.3.34

5.3 Data Collection

Primary data came from three major consumer electronics manufacturers, designated as Manufacturer A (smartphones), Manufacturer B (laptops), and Manufacturer C (smart home devices). Companies provided detailed cost structures, production processes, automation levels, and supply chain configurations for both existing offshore facilities and potential reshoring scenarios.

Secondary data included labor cost statistics from national statistical agencies, transportation cost indices from logistics providers, automation technology costs from equipment suppliers, and tariff schedules from trade databases. All cost data was normalized to 2024 US dollars to enable consistent comparison.

5.4 Simulation Scenarios

The digital twin was used to simulate multiple reshoring scenarios for each product category. Baseline scenarios replicated current offshore production in China or Vietnam. Reshoring scenarios modeled production in the United States and Poland (representing North American and European reshoring destinations). Each location scenario was further subdivided by automation level: current automation (matching offshore facilities), moderate automation (50% increase in automated processes), and high automation (80% increase in automated processes). Each scenario was simulated across 1,000 iterations with varying supply chain conditions including demand fluctuations, transportation delays, and disruption events. This Monte Carlo approach generates probability distributions for cost and performance metrics rather than single-point estimates.

5.5 Analysis Methods

Simulation outputs were analyzed using multiple techniques. Cost competitiveness was assessed through total cost of ownership calculations comparing all-in costs per unit across scenarios. Financial viability used net present value and internal rate of return metrics incorporating automation investment requirements. Supply chain resilience was measured through disruption impact scores and recovery time estimates. Sensitivity analysis identified which parameters most strongly influence reshoring viability.

5.6 Limitations

Several limitations warrant acknowledgment. The model relies on cost and operational data from three manufacturers, which may not represent the entire industry. Simulation accuracy depends on parameter estimates that carry inherent uncertainty. The model captures economic and operational factors but cannot fully quantify strategic considerations like innovation capacity or brand perception. Finally, the analysis reflects 2024 conditions; future changes in technology costs, trade policies, or supply chain structures could alter conclusions.

ANALYSIS OF SECONDARY DATA

6.1 Global Manufacturing Cost Trends

Analysis of manufacturing cost data from 2015-2024 reveals significant shifts in relative competitiveness across regions. Chinese manufacturing labor costs increased by 64% during this period, substantially eroding the historical cost advantage that drove initial offshoring. Vietnamese costs rose more moderately at 38%, but this country also faces capacity constraints and infrastructure limitations. Simultaneously, automation technology costs declined by approximately 42%, making advanced manufacturing systems increasingly accessible.

Transportation costs showed high volatility but generally upward trends. Container shipping costs from Asia to North America averaged $2,800 in 2019 but peaked above $15,000 in 2021 before settling around $5,200 in 2024—still nearly double pre-pandemic levels. These elevated costs significantly impact the economics of shipping bulky, low-value electronics from distant manufacturing locations.

Tariff structures added another cost layer. Average tariffs on consumer electronics imported to the United States from China increased from 3.1% to 18.7% between 2018 and 2024 due to trade policy changes. European Union tariffs remained more stable but still averaged 4-6% on most electronics categories.

DOI: 10.46121/pspc.54.3.34

[TABLE 1: Comparative Manufacturing Costs by Region (2024)]

Cost Category	China	Vietnam	United States	Poland
Hourly Labor Cost ($)	6.80	3.90	28.50	14.20
Electricity ($/kWh)	0.08	0.09	0.11	0.13
Factory Lease ($/sq.m/year)	95	68	142	108
Logistics to US Market ($)	5,200	4,900	850	3,100
Average Tariff (%)	18.7	8.2	0	0

Note: Labor costs represent manufacturing sector averages including benefits; Logistics costs represent 40-foot container shipping to major US distribution centers; Factory lease costs based on industrial zone averages

6.2 Automation Technology Trends

Automation technology costs and capabilities have evolved rapidly. Industrial robot prices declined from an average $46,000 per unit in 2015 to $27,000 in 2024 for standard models, while performance metrics like speed, precision, and flexibility improved substantially. Collaborative robots (cobots) designed to work alongside humans dropped from $35,000 to $18,000 over the same period, making automation accessible to smaller production runs.

However, automation investment extends beyond robot purchases to include system integration, programming, maintenance infrastructure, and workforce training. Total automation implementation costs typically run 3-4 times the equipment purchase price, creating significant capital requirements. For consumer electronics assembly lines, achieving 80% automation levels requires investments of $15-25 million depending on product complexity and production volume.

6.3 Supply Chain Disruption Patterns

Analysis of supply chain disruption data from 2020-2024 quantifies risks in offshore production models. Major disruptions—defined as events causing production delays exceeding 2 weeks—occurred at an average frequency of 1.8 events per year for manufacturers relying on Chinese production, compared to 0.6 events per year for those with North American facilities. Average disruption duration was 6.2 weeks for Asian supply chains versus 2.8 weeks for domestic production.

These disruptions carried substantial financial costs. Revenue losses during supply interruptions averaged $12-18 million per week for large manufacturers, while rushed alternative sourcing added 35-60% cost premiums. Inventory buildup to buffer against disruptions created additional carrying costs of 18-24% annually on safety stock value.

ANALYSIS OF PRIMARY DATA - DIGITAL TWIN SIMULATION RESULTS

7.1 Baseline Production Economics

Digital twin simulations of current offshore production established baseline economics for comparison. For smartphones (Manufacturer A), offshore production in China yielded total costs of $142 per unit including $68 in component costs, $31 in assembly labor, $18 in overhead, $14 in transportation and tariffs, and $11 in inventory carrying costs. Laptops (Manufacturer B) showed similar patterns with $386 total unit costs. Smart home devices (Manufacturer C) averaged $47 per unit due to simpler assembly requirements.

These baselines incorporate not just direct production costs but also supply chain expenses often overlooked in simplistic cost comparisons. Transportation and tariffs alone represented 9.9% of total smartphone costs, while inventory costs from 45-day average supply chain lead times added another 7.7%. These "hidden" offshore costs total approximately 18% of product costs, substantially higher than typically assumed.

7.2 Reshoring Scenario Economics

Simulation of reshoring scenarios revealed significant variations by product type and automation level. For smartphones with current automation levels, US reshoring increased total unit costs to $178 (+25% versus offshore baseline), primarily driven by labor cost differentials. However, with high automation, US production costs declined to $151 (+6% versus offshore), approaching cost parity. The automation investment required was approximately $22 million for a facility producing 2 million units annually.

DOI: 10.46121/pspc.54.3.34

Laptops showed different patterns. Current automation reshoring to the US increased costs to $445 (+15% versus offshore), but high automation reduced this to $398 (+3% versus offshore). The larger product size and lower production volumes meant transportation savings from reshoring were more substantial, offsetting labor cost increases more effectively than for smartphones.

Smart home devices demonstrated strongest reshoring viability. Even with current automation, US production cost $53 (+13% versus offshore), while high automation achieved $44 (actually 6% below offshore baseline). The combination of lower product value, high shipping costs relative to product price, and simple assembly processes created favorable reshoring economics.

[TABLE 2: Simulation Results - Total Unit Costs by Scenario ($)]

Product	Offshore Baseline	US - Current Auto	US - High Auto	Poland - Current Auto	Poland - High Auto
Smartphone	142	178	151	162	138
Laptop	386	445	398	418	381
Smart Device	47	53	44	49	42
Cost Change (%)	--	+15.5%	+3.2%	+10.2%	-1.8%

Note: Values represent simulation averages across 1,000 iterations; Current Auto maintains existing automation levels; High Auto represents 80% increase in automated processes; Poland represents European reshoring option

7.3 Supply Chain Performance Metrics

Beyond pure cost economics, digital twin simulations quantified supply chain performance differences across scenarios. Average lead times from order to delivery decreased from 47 days in offshore scenarios to 12 days in US reshoring scenarios—a 74% reduction. This lead time compression enabled inventory reductions of 55%, substantially lowering working capital requirements.

Supply chain disruption modeling revealed reshoring's resilience benefits. Offshore scenarios experienced simulated major disruptions in 23% of annual cycles, causing average revenue losses of $8.4 million per disruption event. Reshored scenarios showed disruption frequency of only 7% with average losses of $2.1 million per event. The expected annual disruption cost therefore declined from $1.93 million for offshore production to $0.15 million for reshored production.

However, reshoring introduced new vulnerabilities. Offshore facilities benefited from supplier ecosystem density, with alternative component sources readily available. Reshored facilities faced less developed supplier networks, creating dependency on fewer vendors. The simulation revealed that while disruption frequency decreased with reshoring, recovery times for certain disruption types actually increased due to limited alternative sourcing options.

7.4 Automation Impact Analysis

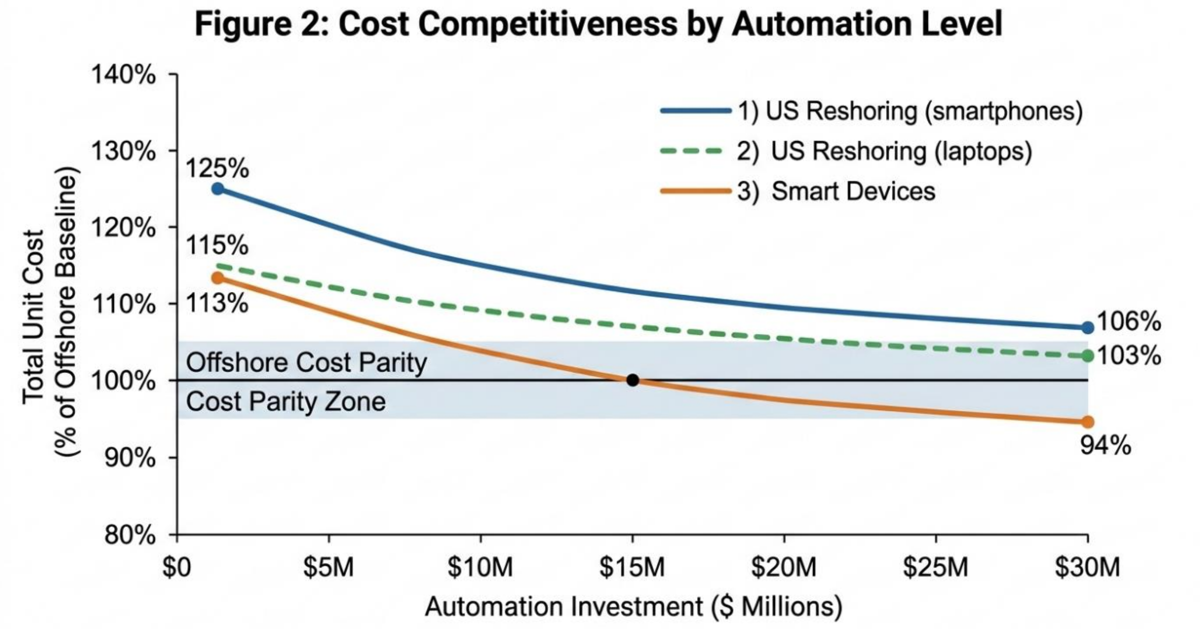
Detailed analysis of automation's role in reshoring viability revealed clear patterns. For every $1 million in automation investment, average unit costs declined by $0.42-0.68 depending on product complexity and production volumes. However, these benefits followed a curve of diminishing returns—initial automation investments (0-40% of processes) yielded cost reductions of approximately $0.65 per $1 million invested, while advanced automation (60-80% of processes) yielded only $0.38 per $1 million.

The breakeven analysis showed that automation investments for reshoring became financially viable when production volumes exceeded certain thresholds. For smartphones, the automation investment required for cost-competitive reshoring achieved positive NPV at production volumes above 1.8 million units annually with a 4.2-year payback period. Laptops required 850,000 annual units for viability with 5.1-year payback. Smart home devices showed the most favorable economics, reaching breakeven at 1.2 million units with 3.6-year payback.

Labor content analysis revealed why automation impacts varied by product. Smartphones required 42 minutes of direct labor per unit in baseline offshore production, while high automation reduced this to 6 minutes—an 86% reduction. However, since labor represented only 22% of total costs, this dramatic labor reduction translated to

DOI: 10.46121/pspc.54.3.34

just 19% total cost savings. For smart devices with higher labor content (31% of costs), similar automation levels achieved 24% total cost reductions.



[FIGURE 2: Cost Competitiveness by Automation Level]

This line graph displays the relationship between automation investment and total unit costs across different reshoring scenarios. The x-axis shows automation investment levels from $0 to $30 million in $5 million increments. The y-axis shows total unit cost as a percentage relative to offshore baseline, ranging from 80% to 140%. Four distinct lines represent different scenarios: US Reshoring (smartphones) starts at 125% with zero automation and declines to 106% at maximum automation, shown as a solid blue line. US Reshoring (laptops) begins at 115% and decreases to 103%, represented by a dashed green line. Smart Devices start at 113% and decline to 94%, shown as a solid orange line. A horizontal reference line at 100% marks cost parity with offshore production. The graph clearly illustrates diminishing returns to automation investment—the lines show steeper declines initially that flatten at higher investment levels. A shaded region between 95-105% is labeled "Cost Parity Zone." The graph includes a legend identifying each product line and key breakeven points marked with dots.

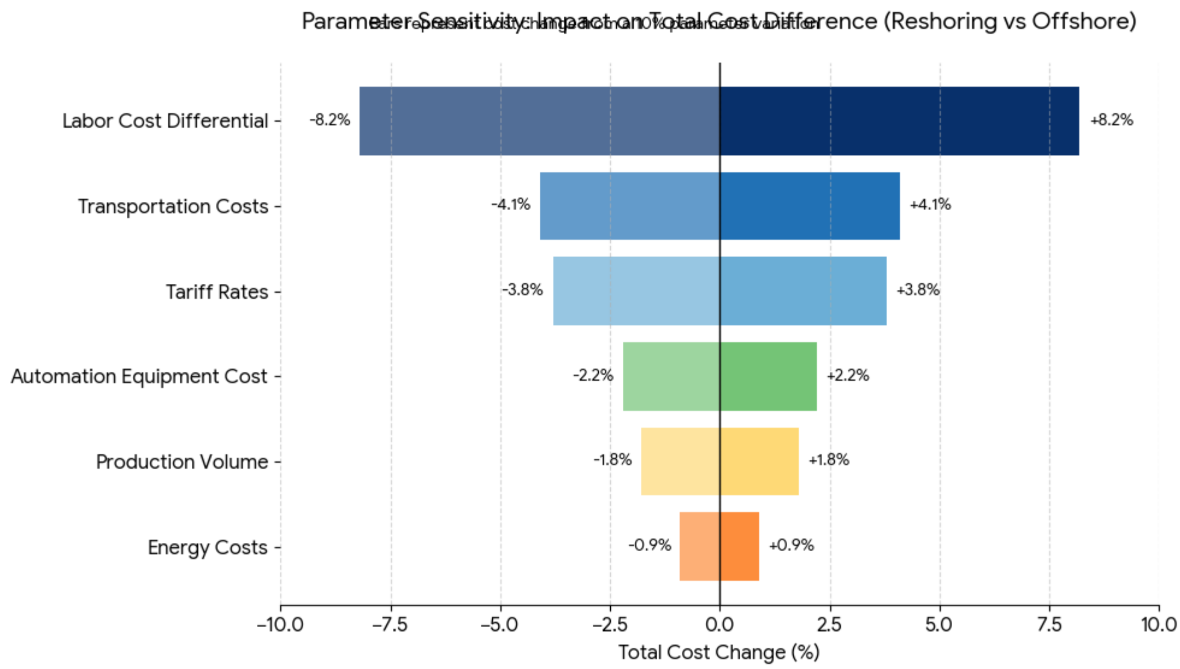
7.5 Sensitivity Analysis

Sensitivity analysis identified which parameters most strongly influence reshoring viability. Labor cost differential emerged as the dominant factor, with a 10% change in wage gaps shifting total costs by 4.2-6.8% depending on automation levels. Transportation costs ranked second—a 10% change in shipping costs altered total costs by 1.8-3.4%, with greater impact on lower-value products. Tariff rates showed 1:1 relationships with cost changes, meaning a 10 percentage point tariff increase directly added 10% to landed costs of imported products.

Automation technology costs demonstrated moderate sensitivity. A 10% decline in automation equipment prices improved reshoring economics by reducing total costs by 0.8-1.4%, meaningful but insufficient to fundamentally alter viability conclusions. Production volumes showed threshold effects—below certain volumes, fixed automation costs made reshoring unviable regardless of other parameters, while above thresholds, reshoring became increasingly attractive.

DOI: 10.46121/pspc.54.3.34

Power System Protection and Control
ISSN:1674-3415



[FIGURE 3: Sensitivity Analysis - Impact on Reshoring Viability]

This tornado chart displays the relative impact of different parameters on reshoring cost competitiveness. The chart is arranged horizontally with a central vertical axis at 0% cost change. Each parameter is represented by a horizontal bar extending both left (negative impact) and right (positive impact) from the center. The bars are ordered from largest total impact at the top to smallest at the bottom. Labor Cost Differential shows the widest bar, extending from -8.2% to +8.2%, colored in dark blue. Transportation Costs is second with -4.1% to +4.1% in medium blue. Tariff Rates extends -3.8% to +3.8% in light blue. Automation Equipment Cost shows -2.2% to +2.2% in green. Production Volume displays -1.8% to +1.8% in yellow. Energy Costs has the smallest range at -0.9% to +0.9% in orange. Each bar is labeled with the parameter name on the left and percentage ranges on both ends. The chart title reads "Parameter Sensitivity: Impact on Total Cost Difference (Reshoring vs Offshore)" with a subtitle explaining that bars represent cost change from a 10% parameter variation.

DISCUSSION

8.1 Interpretation of Findings

The digital twin simulation results provide nuanced insights into reshoring viability that challenge simplistic narratives. Complete reshoring with current automation levels remains economically unviable for most consumer electronics, with cost premiums of 10-25% making competitiveness impossible. However, selective reshoring combined with substantial automation investment can achieve cost parity or even cost advantages for specific product categories.

The finding that smart home devices show strongest reshoring potential while smartphones remain most challenging reflects fundamental product economics. High-value, compact products like smartphones can absorb transportation costs easily, making geography less important. Lower-value, bulkier products like smart speakers face transportation costs representing 15-20% of product value, creating strong incentives for production near markets.

The supply chain resilience benefits of reshoring proved substantial but difficult to quantify in traditional financial terms. Reduced disruption frequency and faster recovery times create value through revenue protection and reduced emergency costs, but these benefits materialize irregularly rather than as consistent cash flows. Manufacturers must therefore weigh certain cost increases against uncertain but potentially catastrophic disruption risks.

DOI: 10.46121/pspc.54.3.34

8.2 Theoretical Implications

This research advances reshoring theory by demonstrating that location decisions cannot be reduced to simple labor cost arbitrage. The digital twin framework reveals how production economics emerge from complex interactions between labor, capital, logistics, inventory, and disruption risks. Automation fundamentally alters these relationships by changing the relative importance of different cost components.

The findings support portfolio theory approaches to global production networks. Rather than binary offshore-versus-reshore choices, optimal strategies likely involve hybrid models with different products, production stages, or market-serving facilities located based on specific economic and strategic criteria. Digital twin optimization provides the analytical tools to design such portfolio approaches systematically.

8.3 Practical Implications

For consumer electronics manufacturers, the research provides actionable decision frameworks. Products with high shipping costs relative to value, substantial tariff exposure, or time-sensitive market requirements show strongest reshoring potential. Companies should prioritize these categories for detailed reshoring analysis using digital twin or similar comprehensive modeling approaches.

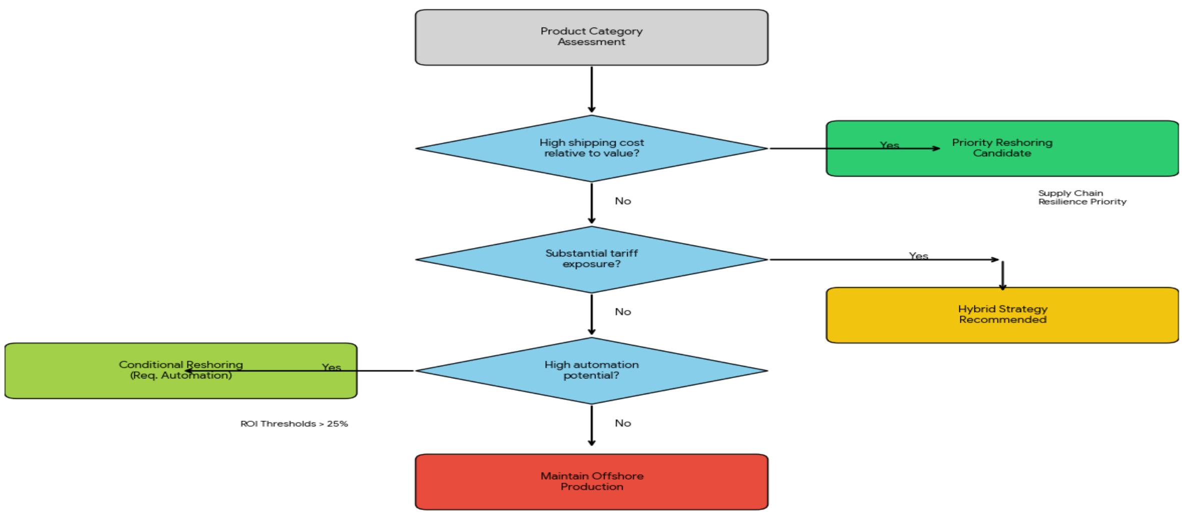
Automation investment emerges as the critical enabler but requires careful financial analysis. The upfront capital requirements are substantial—$15-25 million for typical electronics assembly facilities—and must be justified through either cost savings, volume growth, or risk reduction benefits. Manufacturers should pursue automation whether reshoring or not, as technology costs continue declining while labor costs rise globally.

Supply chain design requires rethinking beyond cost minimization. The pandemic demonstrated that optimizing purely for cost creates brittle systems vulnerable to disruptions. Incorporating resilience metrics alongside cost in location decisions—precisely what digital twin frameworks enable—leads to more robust strategies balancing efficiency with reliability.

8.4 Limitations and Future Research

This study's limitations suggest several research directions. The digital twin model could be enhanced with dynamic market demand modeling, currency exchange rate fluctuations, and political risk factors. Longitudinal studies tracking actual reshoring implementations would validate simulation predictions and identify unexpected challenges. Comparative research across additional industries would test whether findings generalize beyond consumer electronics.

Future research should also examine organizational and workforce dimensions of reshoring beyond pure economics. Transitioning to highly automated domestic facilities requires different skill sets, management approaches, and organizational cultures than traditional offshore models. Understanding these human factors is essential for successful reshoring implementation.



[FIGURE 4: Reshoring Decision Framework]

This decision flowchart provides a structured approach for evaluating reshoring viability. Starting at the top with "Product Category Assessment," the chart flows downward through decision diamond shapes and rectangular process boxes. The first decision point asks "High shipping cost relative to value?" with Yes leading to "Strong Reshoring Candidate" and No proceeding to the next decision. The second decision asks "Substantial tariff exposure?" The third decision evaluates "High automation potential?" The flowchart branches through various paths, ultimately leading to one of four outcomes shown in colored boxes at the bottom: "Priority Reshoring Candidate" (dark green), "Conditional Reshoring - Requires Automation Investment" (light green), "Hybrid Strategy Recommended" (yellow), or "Maintain Offshore Production" (red). Annotations along the paths indicate key considerations like production volume requirements, automation ROI thresholds, and supply chain resilience priorities. The flowchart uses clear visual hierarchy with decision diamonds in blue, process boxes in gray, and outcome boxes in color-coded rectangles.

CONCLUSION

This research demonstrates that consumer electronics reshoring viability depends fundamentally on the interplay between product characteristics, automation levels, and supply chain configurations rather than any single factor. The digital twin optimization framework developed here enables comprehensive evaluation of these complex relationships, moving beyond simplistic cost comparisons to capture true economic trade-offs.

The analysis achieves its primary objective by quantifying reshoring economics across product categories and automation scenarios, revealing that selective reshoring with high automation can achieve cost parity while delivering supply chain resilience benefits. Secondary objectives were similarly met through identification of key cost drivers, comparison of reshoring strategies, evaluation of automation impacts, and development of evidence-based recommendations.

Three critical findings emerge from this research. First, automation investment serves as the primary mechanism making reshoring economically viable, reducing labor cost differentials to manageable levels while improving quality and flexibility. Second, product characteristics—particularly value-to-weight ratios and assembly complexity—create substantial heterogeneity in reshoring potential across electronics categories. Third, supply chain resilience benefits, while difficult to quantify, can justify modest cost premiums particularly given recent disruption experiences.

The digital twin methodology proves valuable for strategic manufacturing location decisions. Traditional analysis tools struggle to capture the dynamic, interconnected nature of modern supply chains. Digital twins enable holistic evaluation incorporating production economics, logistics networks, inventory dynamics, and disruption scenarios in unified frameworks. This capability becomes increasingly important as supply chains face mounting complexity and uncertainty.

Manufacturers should adopt portfolio approaches to production location rather than wholesale reshoring or continued complete offshoring. Different products, components, or production stages may warrant different locations based on specific economic and strategic factors. High-value, low-volume products with substantial automation potential show strongest reshoring candidates. Commodity products with extreme price sensitivity likely require continued offshore production even with automation. Hybrid strategies combining offshore component production with final assembly near markets may optimize both cost and responsiveness.

The automation imperative extends beyond reshoring decisions. Whether maintaining offshore facilities or reshoring production, manufacturers must invest heavily in advanced manufacturing technologies to remain competitive. Labor cost advantages in traditional offshore locations continue eroding while automation costs decline, making technology adoption increasingly essential regardless of geography.

Policy implications suggest that government initiatives supporting reshoring should focus on automation infrastructure rather than direct subsidies. Tax incentives for manufacturing technology investments, workforce training programs for advanced manufacturing skills, and research funding for production innovation would enable broader reshoring than location-specific subsidies. Infrastructure investments in logistics networks, reliable energy supply, and digital connectivity create foundation conditions for competitive domestic manufacturing.

DOI: 10.46121/pspc.54.3.34

Power System Protection and Control
ISSN:1674-3415

Looking forward, consumer electronics manufacturing will likely evolve toward distributed production networks rather than concentrated offshore hubs. This transition will unfold over years or decades rather than immediately, as manufacturers gradually shift production for products where economics justify relocation while maintaining offshore capacity for other categories. Digital twin optimization frameworks will play central roles in guiding these strategic transitions.

This research contributes methodologically by developing integrated digital twin frameworks for strategic location analysis and practically by demonstrating that selective, strategically planned reshoring can be economically viable in consumer electronics despite conventional wisdom suggesting otherwise. The path forward requires neither wholesale reshoring nor continued pure offshoring, but rather thoughtful portfolio approaches guided by comprehensive analytical frameworks that capture the full complexity of global production economics.

REFERENCES

1. https://www.gjesr.com/April-2017.html
2. https://www.gjesr.com/April-2018.html
3. https://ieeexplore.ieee.org/document/11483386
4. Navin Chhibber, Multi-Granular Attention-Driven Reinforcement Learning Framework for Web Intelligent Enhancement Systems, 11 June 2026, https://ieeexplore.ieee.org/document/11483386
5. **https://pspac.info/index.php/dlbh/article/view/447**
6. **https://pspac.info/index.php/dlbh/article/view/439**
7. **https://pspac.info/index.php/dlbh/article/view/440**
8. **https://pspac.info/index.php/dlbh/article/view/445**
9. **https://pspac.info/index.php/dlbh/article/view/448**
10. **https://pspac.info/index.php/dlbh/article/view/452**
11. **https://pspac.info/index.php/dlbh/article/view/451**
12. **https://pspac.info/index.php/dlbh/article/view/465**
13. **Rangavinay Teja Royal Jagga** , 2026, https://ieeexplore.ieee.org/document/11448495
14. **Rangavinay Teja Royal Jagga , 2026, https://ieeexplore.ieee.org/document/11448514**
15. **Rangavinay Teja Royal Jagga , 2026, https://ieeexplore.ieee.org/document/11448337**
16. **Rangavinay Teja Royal Jagga , 2026, https://ieeexplore.ieee.org/document/11497560**
17. **Harnessing Artificial Intelligence Cybersecurity:** Cutting Edge Collaboration of SAP AWS to Safeguard Life Science Data. 2026 https://doi.org/10.1109/aiei69164.2026.11497833
18. **SAP Cloud System on AWS for Risk Detection and Integration Artificial Intelligence Scalable** Cybersecurity 2026 https://doi.org/10.1109/aiei69164.2026.11497435
19. **SAP System Optimization Using AI-Driven Process Automation and Predictive Modeling Maintenance for Enhanced Business Efficiency. 2025** https://doi.org/10.1109/computingcon64838.2025.11376613
20. https://ieeexplore.ieee.org/abstract/document/11376613
21. https://ieeexplore.ieee.org/abstract/document/11497833
22. https://ieeexplore.ieee.org/abstract/document/11497435
23. **https://pspac.info/index.php/dlbh/article/view/231**
24. **https://pspac.info/index.php/dlbh/article/view/235**
25. **https://pspac.info/index.php/dlbh/article/view/232**
26. **https://eudoxuspress.com/index.php/pub/article/view/2236**

27. **Yeasmin, S., Semi, M. M. A., Rony, M. K. K., Das, S., Sabeena, A. A., Rahman, R., Biswas, B., Ahmed, F., & Hossain, A. (2025).** Artificial Intelligence for Mental Health Monitoring: A Solution for Digital Behavioral Health Care and Education—An Umbrella Review. Health Science Reports, 9(1), e71703. https://doi.org/10.1002/hsr2.71703
28. **Hasan, S., Rahman, K. A., Ahmed, F., & Hossain, A. (2026). An integrated AI-driven framework for** maternal resource intelligence shortages across U.S. hospitals. Integrative Biomedical Research, 10(1), 1–8. https://doi.org/10.25163/biomedical.10110694
29. **Riipa, M. B., Ahmed, F., Rony, M. K. K., Hossain, A., Islam, A., Utsho, M. R., Kamal, M. B., Sharmin, S., &** Tasnim, A. F. (2026). The role of artificial intelligence in predicting cardiovascular outcomes: a systematic review and meta-analysis. Biostatistics & Epidemiology, 10(1). https://doi.org/10.1080/24709360.2026.2670804
30. **Semi, M. M. A., Das, S., Utsho, M. R., Hossain,** A., Kamal, M. B., Sizan, A. A., Tasnim, A. F., Yeasmin, S., & Parvin, M. R. (2026). Artificial Intelligence in Public Health Education: A Scoping Review of workforce competency development. Health Science Reports, 9(3). https://doi.org/10.1002/hsr2.72066
31. **Ahmed, F., Hasan, S., Hossain, A., & Rahman, K. A. (2026). Explainable AI framework for detecting and reducing health disparities in healthcare** supply chains. Journal of AI, ML and DL, 2(1), 1–8. https://doi.org/10.25163/ai.2110685
32. **https://eudoxuspress.com/index.php/pub/article/view/5673**
33. **https://eudoxuspress.com/index.php/pub/article/view/5676**
34. **https://eudoxuspress.com/index.php/pub/article/view/5675**
35. **https://pspac.info/index.php/dlbh/article/view/414**
36. **https://eudoxuspress.com/index.php/pub/article/view/5689**
37. **Hima Bindu Lekkala, VishnuVardhan Bandar**i , AUTONOMOUS WORKFLOW OPTIMIZATION USING MULTI AGENT AI SYSTEMS AI AGENTS MANAGE STATIONS, WIP, AND TASK HANDOFFS, Vol. 54 No. 2 (202): April-June 2026, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/306 , DOI: https://doi.org/10.46121/pspc.54.2.08
38. **Lekkala, H. B., & Bandari, V. V. (2026). Autonomous workflow optimization using multi-agent AI systems:** AI agents manage stations, WIP, and task handoffs. *Power System Protection and Control*, 54(2), 95–101. http://pspac.info/index.php/dlbh/article/view/306
39. **Bandari, V. V., & Lekkala, H. B. (2024). Physics-informed reinforcement learning for real-time control of complex manufacturing processes**. *Power System Protection and Control*, 52(2), 164–170. https://pspac.info/index.php/dlbh/article/view/343
40. **Lekkala, H. B., & Bandari, V. V. (2025). AI-based energy-aware scheduling and process optimization** in engineer-to-order smart manufacturing systems. *Power System Protection and Control*, 53(1), 30–36. http://pspac.info/index.php/dlbh/article/view/341
41. **Bandari, V. V., & Lekkala, H. B. (2026). AI-driven digital** thread framework for end-to-end lifecycle optimization in ETO manufacturing systems. *Power System Protection and Control*, 54(2), 318–325. http://pspac.info/index.php/dlbh/article/view/340

42. **Lekkala, H. B., & Bandari, V. V. (2026). Deep learning** for weld defect detection using CNN or vision transformers fusion detection. *Power System Protection and Control*, 54(2), 151–158. https://pspac.info/index.php/dlbh/article/view/314
43. **Bandari, V. V., & Lekkala, H. B. (2024). AI-based operator** behavior monitoring and cost optimization using digital traceability in manufacturing systems. *Power System Protection and Control*, 52(1), 38–45. https://pspac.info/index.php/dlbh/article/view/342
44. **Shreyas Jayaprakash,** MACHINE LEARNING-DRIVEN VERIFICATION: USING ML TO OPTIMIZE COVERAGE ANALYSIS, PREDICT SIMULATION RUNTIMES, AND AUTO-GENERATE TESTBENCHES, Vol. 54 No. 2 (2026): April-June 2026, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/391
45. **Mohammed Shafi Kundiladi,** EVENT-DRIVEN IMAGE AND VEHICLE STATUS MANAGEMENT FOR LOW-POWER IOT DIGITAL LICENSE PLATES, Vol. 53 No. 3 (2025): July-September 2025, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/175 DOI: https://doi.org/10.46121/pspc.53.3.17
46. Controlled Synthesis and Characterization of Lanthanum Nanorods, **Author(s), Jayadeep Tejani, Rahul Shah, Hiral Vaghela, Shailesh Vajapara, Amanullakhan Pathan**, doi:10.18576/ijtfst/090205, URL: https://www.naturalspublishing.com/Article.asp?ArtcID=20705, May-2020
47. **Kunal Kapoor**, **Apr 2026,** Relation Extraction and NER through Fine Tuned BERT model with transfer Learning, https://ieeexplore.ieee.org/document/11472214/metrics#metrics
48. **Harender Bisht**, Human–AI Collaboration in Insurance Fraud Detection: Ethical Cloud-Native Architectures for Fair and Transparent Decision Support, **Volume 2026, Issue 1,** https://doi.org/10.52710/cfs.873
49. **Harender Bisht,** Ethical AI-Augmented Compliance Systems: Architectural Innovations for Cloud-Native Financial and Insurance Data Integrity, **Vol. 11 No. 1s (2026) ,** https://doi.org/10.52783/jisem.v11i1s.14056
50. **Harender Bish**t, Governance-By-Design For AI-Based Insurance Fraud Detection: Auditability, Accountability, And Regulatory Traceability, **Archives / Vol. 9 No. 1 (2026**) ,https://doi.org/10.63278/jicrcr.vi.3620
51. **Harender Bisht,** Operationalizing Explainable AI in Insurance Fraud Detection: From Model Transparency to Decision Justification, **Vol. 35 No. 1 (2026): JOCAAA**, https://eudoxuspress.com/index.php/pub/article/view/4791,
52. **A. MahendraVardhan and S. Sridhar,** "Determining False Positive Analysis of Software Vulnerabilities with Predefined Scan Rules using Random Forest Classifier and Decision Tree Technique," **2022 4th International Conference on Advances in Computing**, Communication Control and Networking (ICAC3N), Greater Noida, India, 2022, pp. 622-625, **DOI: https://doi.org/10.1109/ICAC3N56670.2022.10074458**
53. **Amilineni, M.V. 2025**. Audit-Safe Agentic RAG Framework for Regulated Enterprise Systems: A Trustworthy AI Architecture for SAP, Finance, Healthcare, and Government Workflows.

INTERNATIONAL JOURNAL OF ADVANCES IN SIGNAL AND IMAGE SCIENCES. (Jan. 2025), 34– **DOI:** https://doi.org/10.29284/7fjzk883

54. **Deepa Nagalavi; Shankar Balla Microsoft, USA; Pushpalatha. M; Nashwan Adnan Othman; Malik Bader Alazzam; A. Balakumar,** Enhancing Real-Time Language Processing via Advanced PET Signal Analysis and Deep Learning, ***06-07 June 2025***, DOI: 10.1109/ICICKE65317.2025.11136561 , https://ieeexplore.ieee.org/document/11136561
55. https://pspac.info/index.php/dlbh/article/view/430
56. **Venkata Sai Aditya Kondru,FMR, Carmel, USA ,; Shankar Balla; Dhavalkumar Thakar; Dheeraj Velaga; Sri Lekha Bandla,** Intelligent Human–Computer Interaction for Navigation Control Through Vision-Based Hand Gesture Recognition, Conferences >2026 IEEE 15th International , **Date of Conference:** ***07-09 April 2026***,**Date Added to IEEE *Xplore***: 08 May 2026 **DOI:** 10.1109/CSNT69054.2026.11502317 , https://ieeexplore.ieee.org/abstract/document/11502317
57. SUDIPKUMAR GHANVAT , AISHWARYA BADLANI, SHREYA SANDEEP JOSHI, MARKETING EFFECTIVENESS IN THE POST-COOKIE ERA: A COMPARATIVE ANALYSIS OF FIRST PARTY AND ZERO-PARTY DATA STRATEGIES ON CAMPAIGN PERFORMANCE AND CUSTOMER EQUITY, VOL. 31 NO. 4 (2023): JOCAAA , HTTPS://WWW.EUDOXUSPRESS.COM/INDEX.PHP/PUB/ARTICLE/VIEW/3940
58. **Navin Chhibber,; Deepak Singh; Anokh Kishore, Capital One, USA; Nikita Chawla; K. Anguraj,** Multi-Granular Attention-Driven Reinforcement Learning Framework for Web Intelligent Enhancement Systems, , **11 June 2026**, https://ieeexplore.ieee.org/document/11483386
59. https://pspac.info/index.php/dlbh/article/view/456
60. https://pspac.info/index.php/dlbh/article/view/455
61. https://eudoxuspress.com/index.php/pub/article/view/5677
62. Anumolu DPK, Veena B, Afreen SS, Bandla J, Lakshmi KC, Pulusu VS. In vitro models for studying drug metabolites and metabolizing enzymes: A comprehensive review. Int J Pharm Investig. 2026;16(3):885–91. Available from: http://dx.doi.org/10.5530/ijpi.20260116
63. Asgar Z, Kumar G, Khandelwal P, Pratap B, Gurjar V, Baluni A, et al. Utility of contrast-enhanced computed tomography abdomen in Intestinal Obstruction. Int J Drug Deliv Technol. 2026;16(32s). Available from: http://dx.doi.org/10.25258/ijddt.16.32s.4
64. 64: Anumolu DP, Ramatulasi J, Ashok G, Afreen SS, Mathew C, Shakar PV. Synthesis and characterization of MIP ghost approach for selective extraction of empagliflozin and quantification by liquid chromatography. J Chromatogr Sci. 2025;63(2). Available from: http://dx.doi.org/10.1093/chromsci/bmaf008.
65. Anumolu DPK, Naraparaju S, Addada SB, Pagidipally V, Pulusu VS, Afreen SS. Synthesis of silver nanoparticles using Ecbolium ligustrinum leaves: Characterization through advanced analytical techniques. Nanotechnol Percept . 2024;710–8. Available from: http://dx.doi.org/10.62441/nano-ntp.vi.3618
66. Naraparaju S, Mukti A, Anumolu DP, Chaganti S. Development and validation of a spectrofluorimetric method for the quantification of capecitabine in bulk and tablets. Turk J Pharm Sci [Internet]. 2023;20(4):234–9. Available from: http://dx.doi.org/10.4274/tjps.galenos.2022.46364

67. Naraparaju S, Yamjala P, Chaganti S, Anumolu DP. Spectrophotometric quantification of atomoxetine hydrochloride based on nucleophilic substitution reaction with 1,2-naphthoquinone-4-sulfonic acid sodium salt (NQS). Turk J Pharm Sci [Internet]. 2024;20(6):405–11. Available from: http://dx.doi.org/10.4274/tjps.galenos.2022.09147.
68. https://pspac.info/index.php/dlbh/article/view/454
69. https://pspac.info/index.php/dlbh/article/view/449
70. https://pspac.info/index.php/dlbh/article/view/453
71. https://eudoxuspress.com/index.php/pub/article/view/5678
72. A Hybrid Deep Learning and Quantum Optimization Framework for Ransomware Response in Healthcare, DOI: 10.1109/OJCS.2025.3648741, https://ieeexplore.ieee.org/document/11316401, Date of Publication: 26 December 2025, Published in: IEEE Open Journal of the Computer Society,Journal: IEEE.
73. Md Nazmul Shakir Rabbi, Farhana Rahman Anonna, Kazi Nehal Hasnain, Sakib Murshed, Md Fazlul Huq Mithu, MD Tushar Khan, Monoara Begum, Sonia Afroze, HYBRID AI MODELS COMBINING RULES AND MACHINE LEARNING FOR FINANCIAL FRAUD CONTROL IN THE UNITED STATES, Vol. 54 No. 2 (2026): April–June 2026, Power System Protection and Control, https://pspac.info/index.php/dlbh/article/view/334 ,https://pspac.info/index.php/dlbh/article/view/334/271
74. **Adegboye A , O., Li, X., Qian, L. (2025).** Parameterized Model for Fork Antenna Design in UWB Band Using Fully Connected Artificial Neural Networks. In: Arabnia, H.R., Deligiannidis, L., Amirian, S., Shenavarmasouleh, F., Ghareh Mohammadi, F., de la Fuente, D. (Eds) Artificial Intelligence and Applications. CSCE 2024. Communications in Computer and Information Science, vol 2252. Springer, Cham. https://doi.org/10.1007/978-3-031-86623-4_7
75. **Adegboye A. Olaoluwa1, Udofia M. Kufre,Obot Akanniyenne**, Inverted C-Shaped Slots Loaded Exponential Tapered Triple Band Notched Ultra-Wideband (UWB) Antenna, https://doi.org/10.5281/zenodo.18139060, **Published May 31, 2024**
76. **Chander Vijay S Sanbhi**, LEADING-INDICATOR-DRIVEN RELIABILITY MODELLING: INCORPORATING OPERATIONS-DRIVEN RELIABILITY TASKS INTO FAILURE HAZARD ESTIMATION, Vol. 54 No. 2 (2026): April-June 2026, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/376.
77. **Chander Vijay S Sanbhi**, DATA QUALITY AS A RELIABILITY MULTIPLIER: QUANTIFYING THE IMPACT OF STANDARDIZED WORK PROCESSES ON RELIABILITY MODEL ACCURACY, Vol. 52 No. 4 (2024): October-December 2024, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/385
78. **Chander Vijay S Sanbhi,** HYBRID MARKOV–MONTE CARLO RAM MODELLING FOR MULTI-STATE ASSETS WITH NON-EXPONENTIAL FAILURE/REPAIR DISTRIBUTION, Vol. 54 No. 1 (2026): January-March 2026, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/379
79. **Chander Vijay S Sanbhi,** DEGRADATION-AWARE SPARES OPTIMIZATION WITH WEIBULL/PHM UNCERTAINTY AND LOGISTICS DELAYS, Vol. 52 No. 2 (2024): April-June 2024, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/384

80. **Chander Vijay S Sanbhi**, PHYSICS-INFORMED RUL PREDICTION WITH ALEATORIC/EPISTEMIC UNCERTAINTY AND MAINTENANCE SYSTEM INTEGRATION, Vol. 54 No. 1 (2026): January-March 2026, Power System Protection and Control, ISSN-1674-3415 https://pspac.info/index.php/dlbh/article/view/378
81. **Chander Vijay S Sanbhi,** DIGITAL TWIN–RAM CO-SIMULATION FOR MAINTENANCE AND SPARING DECISIONS IN PROCESS FACILITIES, Vol. 52 No. 1 (2024): January-March 2024, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/383
82. **Chander Vijay S Sanbhi**, A JOINT PROBABILISTIC FRAMEWORK TO INTEGRATE RAM SIMULATION AND ECONOMIC FORECASTING WITHOUT DOUBLE-COUNTING DOWNTIME, Vol. 53 No. 4 (2025): October-December 2025, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/394
83. **Chander Vijay S Sanbhi**, MIXTURE-DISTRIBUTION MAINTAINABILITY MODELLING TO CAPTURE TAIL-RISK DOWNTIME IN CRITICAL MACHINERY, Vol. 53 No. 2 (2025): April-June 2025, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/393
84. **Chander Vijay S Sanbhi,** BAYESIAN UPDATING OF RAM MODELS FOR DYNAMIC AVAILABILITY FORECASTING UNDER REALISTIC DOWNTIME CONSTRAINTS**, Vol. 51 No. 3 (2023): July-**September 2023, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/381
85. **Chander Vijay S Sanbhi,** HYBRID RELIABILITY MODELLING FOR ROTATING EQUIPMENT: PHYSICS-INFORMED LEARNING WITH SPARSE FAILURE DATA, Vol. 51 No. 4 (2023): October-December 2023, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/382
86. https://www.atlantis-press.com/proceedings/icsbpim-25/126017621, **23-24 April 2025**
87. https://ieeexplore.ieee.org/abstract/document/11371052 , **2025 2nd International Conf.**
88. https://ieeexplore.ieee.org/abstract/document/11256577
89. https://ieeexplore.ieee.org/abstract/document/11069968
90. https://ieeexplore.ieee.org/abstract/document/11377462
91. Manikantha Varaprasad Inakollu, (2022, August), Decision Intelligence As A Strategic Capability: A New MIS Framework For AI-Driven Enterprises, A Comprehensive Approach To Integrating Artificial Intelligence Into Organizational Decision-Making, Vol. 23 No. 4 (2022), 66–79, Acta Scientiae, ISSN:2178-7727,
URL: https://www.periodicos.ulbra.org/index.php/acta/article/view/662
DOI: https://doi.org/10.22178/acta.23.4.6
92. Manikantha Varaprasad Inakollu, (2022, December), Governance-Centric MIS Architectures For Enterprise-Scale Digital Transformation, Vol. 23 No. 6 (2022), 41-55, Acta Scientiae, ISSN:2178-7727, URL: https://www.periodicos.ulbra.org/index.php/acta/article/view/667
DOI: https://doi.org/10.22178/acta.23.6.4
93. Manikantha Varaprasad Inakollu, (2023, November), Governance-Aware Cloud Architectures For Enterprise Information Systems, Vol. 24 No. 6 (2023), 300-315, Acta Scientiae, ISSN:2178-7727, URL: https://www.periodicos.ulbra.org/index.php/acta/article/view/668

DOI: https://doi.org/10.22178/acta.24.6.28

94. Manikantha Varaprasad Inakollu, (2024, July), Enhancing ERP Auditability and Compliance Using Permissioned Blockchain, A Framework for Transparent and Immutable Enterprise Resource Planning Systems, Vol. 25 No. 3 (2024), 122-137, Acta Scientiae, ISSN:2178-7727, URL: https://www.periodicos.ulbra.org/index.php/acta/article/view/664
DOI: https://doi.org/10.22178/acta.25.3.16
95. Manikantha Varaprasad Inakollu, (2025, November), Quantum-Resilient Architectures for Enterprise and Cloud Information Systems, Implications of Quantum Computing for Enterprise Cybersecurity and Data Integrity, Vol. 26 No. 3 (2025), 580-595, Acta Scientiae, ISSN:2178-7727, URL: https://www.periodicos.ulbra.org/index.php/acta/article/view/663
DOI: https://doi.org/10.22178/acta.26.3.44
96. Manikantha Varaprasad Inakollu, (2023, May), Post-Implementation ERP value realization: A Decision intelligence Framework, Vol. 51 No. 2 (2023): April-June 2023, 48-63, Power System Protection and Control, ISSN-1674-3415,
URL: https://pspac.info/index.php/dlbh/article/view/286
DOI: https://doi.org/10.46121/pspc.51.2.6
97. Manikantha Varaprasad Inakollu, (2023, July), ERP as Digital Backbone: Redefining enterprise systems for continuous value creation, Vol. 51 No. 3 (2023): July-September 2023, 17-29, Power System Protection and Control, ISSN-1674-3415,
URL: https://pspac.info/index.php/dlbh/article/view/285
DOI: https://doi.org/10.46121/pspc.51.3.4
98. Manikantha Varaprasad Inakollu, (2024, May), FINOPS-Driven Cloud optimization models for enterprise applications, Vol. 52 No. 2 (2024): April-June 2024, 99-110, Power System Protection and Control, ISSN-1674-3415,
URL: https://pspac.info/index.php/dlbh/article/view/283
DOI: https://doi.org/10.46121/pspc.52.2.10
99. Manikantha Varaprasad Inakollu, (2025, July), Blockchain-Enabled trust frameworks for enterprise information systems, establishing verifiable trust in distributed organizational environments, Vol. 53 No. 3 (2025): July-September 2025, 285-300, Power System Protection and Control, ISSN-1674-3415, URL: https://pspac.info/index.php/dlbh/article/view/282
DOI: https://doi.org/10.46121/pspc.53.3.19
100. Manikantha Varaprasad Inakollu, (2026, March), Implications of quantum computing for enterprise cybersecurity and data integrity, Vol. 54 No. 1 (2026): January-March 2026, 831-844, Power System Protection and Control, ISSN-1674-3415,
URL: https://pspac.info/index.php/dlbh/article/view/281
DOI: https://doi.org/10.46121/pspc.54.1.57
101. **Pawan Kumar Singh,** Scaling Gate-All-Around (GAA) Transistor Architectures for Sub-2nm AI Accelerators Using Atomically Thin 2D Materials, Vol. 33 No. 08 (2024): JOCAAA, Journal Name: Journal of Computational Analysis and Applications, Journal's ISSN: 1521-1398 (Paper),1572-9206 (Online), https://eudoxuspress.com/index.php/pub/article/view/5713

102. **Pawan Kumar Singh,** Energy-Efficient Task Scheduling in Green Cloud Computing Using Neuromorphic Spiking Neural Networks, Vol. 33 No. 08 (2024): JOCAAA, Journal Name: Journal of Computational Analysis and Applications, Journal's ISSN: 1521-1398 (Paper),1572-9206 (Online), https://eudoxuspress.com/index.php/pub/article/view/5712
103. **Kunal Kapoor**, **Apr 2026,** Relation Extraction and NER through Fine Tuned BERT model with transfer Learning, https://ieeexplore.ieee.org/document/11472214/metrics#metrics
104. **Kapoor K, et al. AI-Driven COVID-19 Care**: Analytics, Scheduling & Geo-Access. International Journal of Drug Delivery Technology (IJDDT). **2026;16 (65S):Article** 136. Available at: https://impactfactor.org/PDF/IJDDT/16/IJDDT,Vol16,Issue65s,Article136.pdf
105. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=7061998
106. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=7062058
107. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=7061858
108. https://doi.org/10.1109/IC2NC67409.2025.11376261
109. https://doi.org/10.1109/ICBATS66542.2025.11258564
110. Rizwana Sindhavani. (2024). Self-Healing Cloud Security Architecture for Financial Systems Using Autonomous Incident Response . Journal of Computational Analysis and Applications (JoCAAA), 33(08), 9186–9197. Retrieved from https://eudoxuspress.com/index.php/pub/article/view/5678
111. Rizwana Sindhavani. (2023). AI-Driven Cyber Threat Intelligence and Real-Time Attack Prevention System for Financial Institutions Using Behavioral Anomaly Detection and Continuous Risk Scoring . Journal of Computational Analysis and Applications (JoCAAA), 31(4), 3055–3066. Retrieved from https://eudoxuspress.com/index.php/pub/article/view/5677
112. Rizwana Sindhavani (2026) Machine Learning Enhanced Credit Risk Assessment Models For Community And Regional Banks : Improving Lending Decisions Through Alternative Data And Presixtive Analytics. Journal of Power System Protection and control 54(3), 197-210. Retrieved from https://pspac.info/index.php/dlbh/search
113. Rizwana Sindhavani (2025) . Adversarially Robust AI Framework For Securing Machine Learning Based Cyber Defense Systems Against Evasion And Poising Attacks In Financial Services . Journal of Power System Protection and Control 53(4) , 588-599. https://pspac.info/index.php/dlbh/search
114. Protecting Helathcare Financial Records And Digital Payment Ecosystems. Journal of Power System Protection and Control 53(2) , 440-451 . https://pspac.info/index.php/dlbh/search
115. https://doi.org/10.30574/ijsra.2022.5.2.0077
116. https://doi.org/10.30574/ijsra.2021.2.1.0047
117. https://doi.org/10.32628/CSEIT1936413
118. https://doi.org/10.32628/CSEIT192142
119. https://doi.org/10.32996/jcsts.2020.2.2.4
120. https://www.academicpublishers.org/journals/index.php/ijdsml/article/view/5958
121. A. Srivastava, "Securing PHI in cloud-based healthcare systems: Challenges, frameworks, and future directions," J. Comput. Anal. Appl., vol. 33, no. 2, Aug. 2024. [Online]. Available: https://www.eudoxuspress.com/index.php/pub/article/view/4349/3190

122. A. Srivastava, "AI-assisted cloud migration of healthcare claims data from legacy systems: A metadata-driven framework," Int. J. Commun. Networks Inf. Secur., vol. 14, no. 3, Nov. 2022. [Online]. Available: https://ijcnis.org/index.php/ijcnis/article/view/8682
123. A. Srivastava, "Enhancing provider and claims data accuracy using artificial intelligence on cloud-native data platforms," J. Comput. Anal. Appl., vol. 31, no. 4, Nov. 2023. [Online]. Available: https://eudoxuspress.com/index.php/pub/article/view/4347/3189
124. A. Srivastava, "A unified framework for secure cloud data management: Integrating governance, metadata intelligence, and privacy controls," J. Inf. Syst. Eng. Manage., vol. 9, no. 2, Apr. 2024. [Online]. Available: https://www.jisem-journal.com/download/45_A_Unified_Framework.pdf
125. A. Srivastava, "Optimizing large-scale data migration for cloud-native architectures," J. Comput. Anal. Appl., vol. 31, no. 2, pp. 652–662, May 2023. [Online]. Available: https://eudoxuspress.com/index.php/pub/article/view/4603
126. https://pmc.ncbi.nlm.nih.gov/articles/PMC11886096/
127. https://diabetesjournals.org/diabetes/article/73/Supplement_1/908-P/156688/908-P-Use-of-DPP4i-SGLT2i-Fixed-Dose-Combinations
128. https://www.sciencedirect.com/science/article/pii/S0019570720300056