ISSN: 2583-9888
DOI: doi.org/10.51219/JAIMLD/shibaji-chandra/689

URF PUBLISHERS
connect with research world

Journal of Artificial Intelligence, Machine Learning and Data Science

https://urfpublishers.com/journal/artificial-intelligence

Vol: 9 & Iss: 3

Research Article

Human-Centric Approaches for AI Diffusion in Enterprise Process Evolution with Advanced Process Mining Capabilities

Shibaji Chandra*

Sr. Director, Enterprise Architecture, SAP America Inc., USA

Citation: Chandra S. Human-Centric Approaches for AI Diffusion in Enterprise Process Evolution with Advanced Process Mining Capabilities. *J Artif Intell Mach Learn & Data Sci 2026* 9(3), 3496-3502. DOI: doi.org/10.51219/JAIMLD/shibaji-chandra/689

Received: 09 July, 2026; **Accepted:** 14 July, 2026; **Published:** 16 July, 2026

***Corresponding author:** Shibaji Chandra, Sr. Director, Enterprise Architecture, SAP America Inc., USA, E-mail: shibajichandra@gmail.com

ABSTRACT

This paper examines empirical studies on human-centric approaches to artificial intelligence (AI) diffusion within enterprise processes, emphasizing how organizations achieve sustainable process evolution through human-AI collaboration. Specifically, we investigate how process mining tools like Signavio and Celonis are enhancing their capabilities with AI-driven process discovery, transformation and optimization. Through a systematic analysis of recent literature and case studies, we identify key organizational, technological and human factors that determine successful AI adoption in process management, demonstrating that human-centric design principles significantly improve implementation outcomes and organizational value creation.

Keywords: Human-centric AI, Process mining, Enterprise process evolution, AI diffusion, Celonis, Signavio, Process discovery, Digital transformation

1. Introduction

Enterprise process management has undergone significant transformation over the past two decades. Process mining has emerged as a transformative discipline[1], utilizing data analysis and computational intelligence techniques to extract knowledge from event logs. However, as organizations adopt increasingly sophisticated AI-driven process intelligence platforms, the question of how to ensure these technologies serve human needs and organizational values has become paramount.

The challenge lies not merely in implementing advanced technologies but in ensuring that AI-driven process management systems augment rather than replace human expertise.

Research demonstrates that organizations successfully adopting AI in process management prioritize human-centric design principles alongside technological sophistication[2]. This paper addresses this critical gap by examining empirical evidence on how organizations can effectively diffuse AI technologies across enterprise processes while maintaining human agency, decision-making capability and organizational learning.

2. Conceptual Framework: Human-Centric AI in Enterprise Process Evolution

2.1. Defining human-centric AI adoption

Human-centric AI represents a paradigm shift from purely technology-driven automation toward systems that augment human capabilities and decision-making. Research by Fenwick, Molnár and Frangos[3] demonstrates that successful AI implementation requires HRM professionals to harmonize AI's technological capabilities with human-centric needs within organizations. The critical distinction is between AI as replacement technology versus AI as augmentation-where human workers and AI systems work collaboratively to achieve superior outcomes.

In the context of enterprise process management, this means designing process mining and discovery tools that enhance analyst capabilities rather than eliminate them[4]. Explainable AI (XAI) becomes essential here, as it enables process analysts and business users to understand and validate AI-generated insights rather than treating the system as a black box[5].

2.2. Organizational readiness and strategic alignment

The Technology-Organization-Environment (TOE) framework has emerged as a useful lens for understanding AI adoption readiness[6]. Organizations implementing process mining tools successfully demonstrate three critical dimensions:

- Technological infrastructure
- Organizational culture
- Change management capabilities and alignment with business strategy.

According to a multi-organizational study examining AI adoption journeys[7], facilitating conditions such as top management support, strategic roadmap clarity, availability of skilled resources and corporate culture significantly influence successful implementation. Similarly organizations leveraging process mining for process optimization must establish clear governance structures, define success metrics and allocate appropriate resources for continuous learning and model refinement.

3. Process Mining: Evolution and AI Integration

3.1. The process mining discipline

Process mining has become integral to business process management across industries[1]. The discipline enables enterprises to:

- Discover business process models automatically from event log data
- Conform actual process behavior against specified procedures
- Identify process variants, bottlenecks and non-compliant behaviors
- Analyze performance-relevant insights for continuous improvement

Research shows that process mining techniques have been successfully applied across healthcare[8], IT incident management[9] and product lifecycle management, consistently producing significant process improvements ranging from 45-98% reduction in critical metrics[10].

3.2. AI-Driven process discovery: Beyond traditional mining

Traditional process mining relied on algorithm-driven discovery of process patterns from event logs. Contemporary AI-driven process discovery extends these capabilities through machine learning, natural language processing and advanced analytics. Organizations implementing next-generation process intelligence systems report transformative gains[11]:

- Real-time decision-making capabilities enabling proactive intervention
- Automated anomaly detection identifying process deviations before escalation
- Predictive insights forecasting process outcomes with unprecedented accuracy
- Intelligent recommendations for process optimization

The integration of AI into process mining fundamentally changes how enterprises understand and improve their operations. Rather than simply documenting what happened, AI-enhanced process mining systems can predict what will happen and recommend what should happen[12].

4. Case Study: AI-Enhanced Process Mining Tools

4.1. SAP signavio: Integrated process intelligence platform

SAP Signavio represents a comprehensive evolution in process intelligence platform design, integrating discovery, modeling, mining and continuous improvement capabilities. Research on Signavio's implementation demonstrates[13]:

Key Capabilities: - Automated process discovery from enterprise system data - Advanced mining algorithms enabling pattern recognition and conformance checking - Performance analysis through configurable parameters and threshold settings - Integration frameworks supporting both real-time and batch processing - Security mechanisms ensuring data protection across operations **(Figure 1)**.

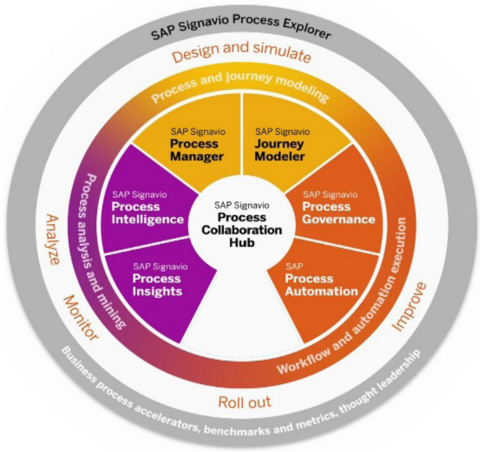

Figure 1: SAP Signavio Process Transformation Suite.

The platform's architecture supports scalable deployments while maintaining security and seamless integration with enterprise systems. Critical to human-centric design, Signavio enables domain experts to validate AI-discovered patterns, apply business logic to algorithmic outputs and maintain interpretability throughout the analysis pipeline.

4.2. Celonis: AI-powered process mining at enterprise scale

Celonis has established itself as a market leader in process mining, particularly through its application of machine learning and AI to extract and visualize process intelligence from enterprise data. Organizations implementing Celonis for process optimization report significant operational improvements[9], with conformance rates as high as 81% and discovery of bottlenecks previously invisible to traditional analysis methods **(Figure 2)**.

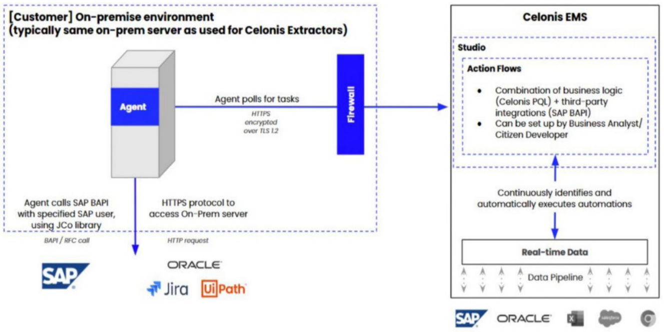

Figure 2: Celonis EMS (Execution Management System) high level architecture for Process Mining setup.

4.3. Implementation evidence

In healthcare applications, Celonis-enabled process mining identified specific bottlenecks in patient consultation and appointment booking processes. Subsequent interventions based on AI-generated insights achieved: - 64% reduction in medical consultation process time - 98% reduction in appointment booking time - Overall 45-46% improvement in process efficiency metrics[10].

Similarly, in IT incident management, Celonis implementations utilizing process discovery and conformance checking techniques enabled organizations to identify process inefficiencies, optimize incident response workflows and improve overall service delivery quality.

5. Empirical Evidence: Organizational Success Factors for AI Diffusion

5.1. Critical enablers of successful implementation

Research examining organizations that have successfully adopted AI in process management identifies twelve critical enablers[14], distributed across three dimensions:

- **Technology dimension (Highest Priority):** Advanced analytics and AI capabilities - Data quality and availability - Integration with existing systems - Scalability and performance.
- **Organizational dimension:** Project management excellence - Change management capability - Executive sponsorship and strategic alignment - Organizational culture supporting innovation.
- **Environmental dimension:** Regulatory alignment and compliance - Industry-specific process requirements - Competitive positioning - Supply chain and stakeholder ecosystem factors.

Analysis reveals that technology dimension enablers carry greatest weight, yet organizational factors often prove decisive in determining implementation success. Organizations lacking change management capability or executive support frequently encounter adoption barriers despite possessing superior technological infrastructure.

5.2. Human-centric design elements

Successful implementations consistently incorporate human-centric design principles[3]:

Augmentation rather than replacement: Process mining tools are positioned as enhancing analyst capabilities rather than automating decisions entirely. Humans retain responsibility for validating, interpreting and acting upon AI-generated insights.

- **Explainability and transparency:** Process analysts receive clear explanations of how AI algorithms selected particular patterns, identified anomalies or recommended optimizations. This transparency builds trust and enables human judgment to override algorithmic suggestions when business context warrants.
- **Participatory design and continuous learning:** Implementation processes incorporate domain experts throughout system design and deployment, ensuring that AI systems learn organizational context and constraints from human expertise.
- **Role transformation rather than role elimination:** Research demonstrates that process analysts, when supported by effective AI tools, transition from routine data processing toward higher-value strategic analysis, exception handling and process innovation activities[2].

5.3. Employee adoption and digital literacy

Organizational research reveals that employee adoption of AI-driven process tools depends significantly on (K. Witara, 2025)[15]:

- Perceived ease of use and intuitiveness of the system interface
- Understanding of how AI recommendations align with organizational values
- Confidence in data security and privacy protections
- Availability of training and ongoing support
- Visibility of positive business outcomes from system use

Organizations implementing comprehensive digital literacy programs targeting both technical skills (using process mining tools effectively) and conceptual understanding (how AI works, its limitations, appropriate use cases) experience dramatically higher adoption rates and more sustained value creation[16].

6. Quantitative Evidence - Human Intervention Benefits in AI-Based Data Mining

6.1. Empirical metrics demonstrating human-in-the-loop superiority

The value proposition of human intervention in AI-based data mining has been validated across multiple domains through rigorous empirical studies. This section presents quantitative evidence demonstrating how human-AI collaboration consistently outperforms fully automated approaches.

6.2. Performance improvements through human feedback

6.2.1. Active learning and human annotation enhancement: Research on human-in-the-loop active learning demonstrates substantial performance gains when human expertise guides model training. A comprehensive study evaluating deep active learning methods found that human-assisted annotation strategies achieve 15-20% better efficiency compared to random selection approaches when combined with semi-supervised learning techniques[26]. The study analyzed 19 different active learning methods, revealing that incorporating human feedback in semi-supervised settings produces consistent performance improvements, especially when abundant unlabeled data is available.

In domain-specific annotation tasks, empirical evidence shows that compact models trained with expert human annotations through active learning outperform large language models despite being hundreds of times smaller[27]. Specifically, small models achieved higher or similar performance to GPT-4 with just a few hundred expert-labeled examples, demonstrating that human domain expertise remains indispensable for tasks requiring specialized knowledge.

6.3. Process mining and enterprise application metrics

6.3.1. Anomaly detection and pattern recognition: In enterprise anomaly detection applications, human-in-the-loop approaches demonstrate substantial performance gains. A study on log-based anomaly detection found that incorporating minimal human knowledge through active learning improved F1-scores by an average of 6.61% with only 5.G% labeled training data[28]. This demonstrates exceptional efficiency-achieving significant accuracy improvements while minimizing the human labeling burden.

In manufacturing quality control, human-augmented inspection frameworks combining AI detection with domain adaptation techniques achieved G3.5% accuracy in real-time anomaly detection[29]. The system demonstrated:

- 58.G% reduction in equipment setup times
- 31.4% decrease in carbon footprint
- 67% reduction in employee safety incidents
- Sub-50ms inference times for real-time applications

The integration of human oversight and feedback mechanisms proved critical to achieving these performance levels while maintaining interpretability and trust[30].

7. Strategic Implementation Framework

7.1. Organizational transformation model

Successful AI diffusion in enterprise process management follows a phased approach **(Figure 3)**:

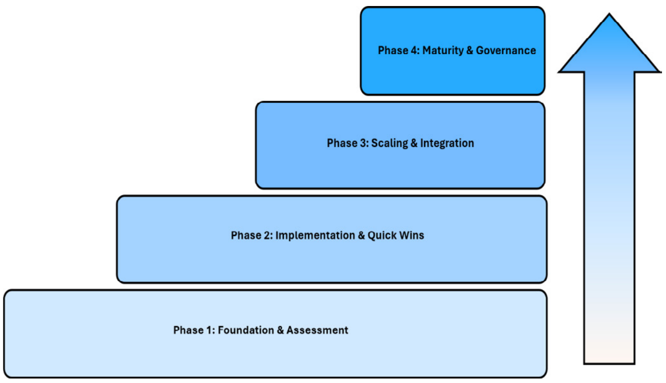

Figure 3: Different Phases of AI Diffusion in enterprise process management.

- **Phase 1:** Foundation s Assessment - Conduct organizational readiness assessment across TOE dimensions - Define clear business objectives and success metrics - Identify pilot processes with high improvement potential - Allocate resources and establish governance structures
- **Phase 2:** Implementation s Quick Wins - Deploy process mining tools in controlled environments - Generate initial process discoveries and validate with domain experts - Demonstrate business value through early wins - Build organizational confidence and momentum
- **Phase 3:** Scaling s Integration - Expand implementation across process portfolio - Integrate process mining insights with enterprise systems - Develop continuous improvement practices - Build organizational capability for ongoing process optimization
- **Phase 4:** Maturity s Governance - Establish governance frameworks ensuring ethical and responsible AI use - Develop advanced analytics and predictive capabilities - Integrate process intelligence with strategic planning - Continuously refine models and expand analytical scope

7.2. Human-centric governance framework

Effective AI governance balances innovation capability with responsible deployment[3]:

7.2.1. Governance elements: Clear policies defining appropriate AI applications in process management - Ethical frameworks ensuring decisions align with organizational values - Transparency mechanisms enabling stakeholder understanding of AI reasoning -Accountability structures assigning responsibility for AI-driven decisions - Continuous monitoring and adjustment mechanisms **(Figure 4)**.

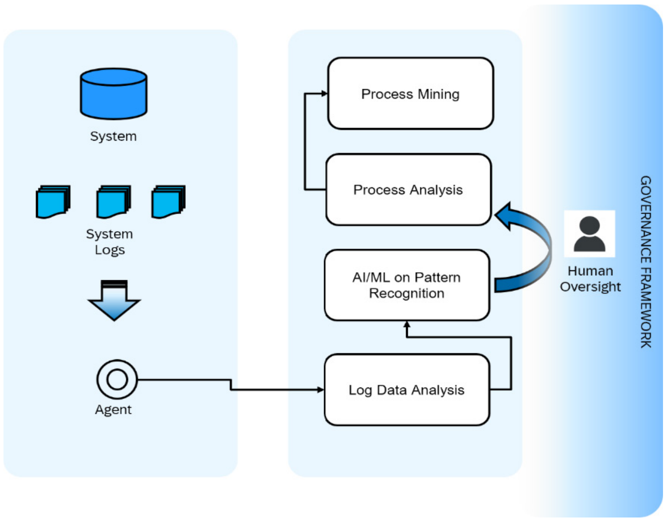

Figure 4: Importance of governance framework in process mining maturity leveraging AI diffusion Human involvement in governance proves critical. Rather than fully automating process recommendations, effective frameworks maintain human oversight, enable challenge of algorithmic recommendations and require documented business justification for significant process changes.

8. Barriers and Challenges to Implementation

8.1. Technical barriers

Organizations implementing process mining and AI-driven process optimization encounter several technical challenges[18]:

- **Data quality and integration:** Event logs often contain inconsistencies, missing values or inadequate granularity. Legacy systems may lack event logging capabilities entirely.
- **Legacy system integration:** Connecting process mining tools to aging enterprise systems requires significant custom development.
- **Algorithmic interpretability:** Advanced machine learning models may generate accurate recommendations but lack clear explanations of their reasoning.
- **Real-time processing:** Many processes generate high-velocity event streams requiring sophisticated infrastructure for real-time analysis.

8.2. Organizational barriers

Research identifies significant organizational barriers to successful implementation (S. Pandey and A. Mishra, 2025):

- **Change resistance:** Employees accustomed to existing processes may resist new AI-driven recommendations, particularly if they perceive threats to job security or professional autonomy.
- **Digital skills gaps:** Organizations often lack sufficient personnel with expertise in process mining, data science and process improvement simultaneously.
- **Resource constraints:** Comprehensive implementation requires sustained investment in technology, training and change management.
- **Competing priorities:** Process mining initiatives compete with other digital transformation efforts for organizational attention and resources.

8.3. Governance and ethical challenges

As process mining and AI become more sophisticated, governance challenges intensify (C. Madduri, 2025)[20]:

- **Algorithmic bias:** Process mining models may perpetuate or amplify existing organizational biases if training data reflects biased historical patterns.
- **Transparency and explainability:** Complex machine learning models may generate accurate predictions but provide insufficient transparency for human decision-makers.
- **Privacy and data security:** Process mining requires access to detailed operational data containing potentially sensitive information about individuals and organizational practices.
- **Autonomy and human agency:** Organizations must maintain appropriate human oversight preventing inappropriate automation of significant process decisions.

8.4. Emerging trends and future directions

8.4.1. Federated learning and privacy-preserving analysis: Next-generation process mining platforms increasingly incorporate federated learning approaches, enabling organizations to gain process intelligence benefits while maintaining data privacy and security. This proves particularly valuable in multi-organizational ecosystems and industries with stringent regulatory requirements.

8.4.2. Process mining and industry 5.0 transition: The shift from Industry 4.0 (automation-centric) toward Industry 5.0 (human-centric) profoundly impacts process mining technology development[21]. Future process mining tools increasingly emphasize:

- Human-Machine Collaboration: Rather than automating decisions, tools augment human analysis and creativity
- Personalized Insights: Process intelligence becomes tailored to individual roles and decision contexts
- Sustainable Operations: Process optimization incorporates environmental and social impact alongside efficiency
- Resilience and Adaptability: Process models incorporate flexibility enabling rapid adaptation to unexpected disruptions.

8.5. Integration with digital twin technology

Process mining increasingly integrates with digital twin technology, enabling organizations to simulate process changes before implementation. This virtual testing capability reduces implementation risk while engaging stakeholders in collaborative scenario analysis[22].

9. Discussion: Synthesizing Evidence on Human-Centric AI Diffusion

The empirical evidence examined in this paper reveals several consistent patterns regarding successful human-centric AI diffusion in enterprise process evolution:

- **Organizational factors matter most:** While technological capability matters organizational readiness-encompassing leadership commitment, change management capability and cultural alignment-most significantly determines implementation success. Organizations with superior technology but inadequate change management consistently underperform those with moderate technology but strong organizational foundations.
- **Human agency must be preserved:** Successful implementations position AI as augmenting human decision-making rather than replacing it. Process analysts, when supported by effective tools and appropriate training, become more valuable, not less valuable, contributing higher-level strategic analysis and exception handling.
- **Governance and ethics cannot be afterthoughts**: Organizations treating governance and ethical frameworks as post-implementation considerations encounter significant challenges. Integrating governance throughout system design, implementation and operation produces more trustworthy, effective and sustainable systems[3].
- **Continuous learning and adaptation:** Process mining and AI-driven optimization are not destinations but ongoing capabilities. Organizations establishing learning systems-where insights inform subsequent process improvements, which generate new data enabling enhanced models-create virtuous cycles of continuous improvement[7].
- **Skills and capabilities must evolve:** Successful organizations invest substantially in developing workforce skills, including both technical capabilities (using process mining tools) and conceptual understanding (how AI works, when to trust algorithmic recommendations, how to identify and correct biases)[16].

10. Practical Recommendations

For Organizational Leaders

- **Establish clear vision and governance:** Define how process mining and AI should contribute to organizational strategy, incorporating ethical frameworks and human-centric principles from inception.
- **Invest in change management:** Allocate resources proportional to technological investment toward change management, training and organizational learning.
- **Prioritize data governance:** Ensure data quality, security and privacy protections enable trustworthy process mining while protecting sensitive information.
- **Maintain human oversight:** Establish mechanisms ensuring humans retain ultimate responsibility for significant process decisions, with AI serving advisory rather than autonomous roles.

For process management professionals

- **Embrace augmentation mindset:** Position process mining tools as enhancing rather than replacing your analytical capabilities. Develop skills in interpreting, validating and acting upon AI-generated insights.
- **Develop analytical skepticism:** Understand AI system limitations, potential biases and appropriate use cases. Validate algorithmic recommendations through business logic and domain expertise.
- **Engage stakeholders:** Actively involve process participants, subject matter experts and affected employees in process mining projects, building understanding and commitment to improvements.
- **Monitor and adjust:** Establish mechanisms for continuous monitoring of process improvements, enabling rapid identification and correction of unintended consequences.

For technology providers

- **Prioritize explainability:** Invest in XAI techniques enabling users to understand algorithmic recommendations and reasoning.
- **Enable governance:** Provide built-in governance capabilities supporting ethics, auditability and human oversight.
- **Support integration:** Ensure seamless integration with existing enterprise systems reducing implementation barriers.
- **Facilitate learning:** Provide training, documentation and community resources supporting effective human-AI collaboration.

11. Conclusion

This research demonstrates that successful AI diffusion in enterprise process evolution depends fundamentally on human-centric approaches balancing technological sophistication with human agency organizational readiness and ethical governance.

Organizations implementing advanced process mining tools like Signavio and Celonis achieve their greatest value not through automation replacing human expertise but through augmentation enabling humans to achieve superior insights and decisions.

Process mining tools enhanced with AI-driven discovery, conformance checking and predictive capabilities represent transformative potential for enterprise process management. Empirical evidence from healthcare, IT operations, manufacturing and other domains demonstrates that properly implemented, these technologies deliver substantial improvements in operational efficiency, quality and strategic responsiveness.

However, realizing this potential requires sustained attention to human factors-organizational readiness, change management, skills development and governance-alongside technological excellence. Organizations treating AI diffusion as purely technological implementation encounter persistent challenges. Those integrating technological capability with human-centric organizational practices achieve the most substantial and sustainable value creation.

As enterprises navigate digital transformation and Industry 5.0 transition, the integration of advanced process mining capabilities with human-centric design principles will increasingly determine competitive advantage. The future belongs not to organizations that most fully automate their processes, but to those that most effectively augment human expertise with intelligent technology systems, creating collaborative human-AI ecosystems driving innovation, efficiency and sustainable value creation.

11. References

1. Brocke J, Jans M, Mendling J, et al. A five-level framework for research on process mining. Business & Information Systems Engineering, 2021.
2. Zaidi SMH, Iqbal R, Alharbi A, et al. Intelligent process automation using artificial intelligence to create human assistant. International Journal of Software Science and Computational Intelligence, 2025.
3. Molnr G, Frangos P. The critical role of HRM in AI-driven digital transformation: A paradigm shift to enable firms to move from AI implementation to human-centric adoption. Discover Artificial Intelligence, 2024.
4. Rogha M. Explain to decide: A human-centric review on the role of explainable artificial intelligence in AI-assisted decision making, 2023.
5. Hassija V, et al. Interpreting black-box models: A review on explainable artificial intelligence. Springer Science+Business Media, 2023.
6. Pumplun L, Tauchert C, Heidt M. A new organizational chassis for artificial intelligence - exploring organizational readiness factors. Technical University of Darmstadt, 2019.
7. Radhakrishnan J, Gupta S, Prashar S. Understanding organizations artificial intelligence journey: A qualitative approach. Association for Information Systems, 2022.
8. Rashed AHM, El-Attar NE, Abd Elminaam DS, et al. Analysis the patients careflows using process mining. Public Library of Science, 2023.
9. Xena, et al. Application of process mining in the process of IT incidents management by utilizing kaggles dataset. Journal of Information Technology and Computer Science, 2023.
10. Julca MARD, Armas-Aguirre J, Mayorga SA. Optimization model for healthcare processes using process mining," Iberian Conference on Information Systems and Technologies, 2023.
11. Selvarajan K. AI-powered big data platforms for enterprise analytics. World Journal of Advanced Engineering Technology and Sciences, 2025.
12. Chennupati N. Cognitive RPA: A framework for hybridizing artificial intelligence with robotic process automation in enterprise systems. European journal of computer science and information technology, 2025.
13. Kolluri S. Leveraging SAP signavio for end-to-end business process transformation: A framework for implementation and usage in intelligent enterprises. Journal of Computer Science and Technology Studies, 2025.
14. Merhi MI, Harfouche A. Enablers of artificial intelligence adoption and implementation in production systems," Taylor & Francis, 2023.
15. Witara K. Pengaruh implementasi artificial intelligence dalam pengelolaan sumber daya manusia terhadap kinerja dan produktivitas: Systematic literature review (SLR), 2025.
16. Morandini S, Fraboni F, Angelis MD, et al. The impact of artificial intelligence on workers skills: Upskilling and reskilling in Organisations. Informing Science Institute, 2023.
17. Younesse O, Soumia Z, Souad LN. Advancing supply chain management through artificial intelligence: A systematic literature review. Indonesian Journal of Electrical Engineering and Computer Science, 2025.
18. Madduri C. AI-driven explainable decisioning in pega: Enhancing transparency across regulated enterprise systems. International journal of research publications in engineering, technology and management, 2025.
19. Ghobakhloo M, Iranmanesh M, Foroughi B, et al. Industry 5.0 implications for inclusive sustainable manufacturing: An evidence-knowledge-based strategic roadmap. Elsevier BV, 2023.
20. Puppala A. The role of digital twins in AI-driven enterprise BI: Transforming scenario simulation and strategic planning. European journal of computer science and information technology, 2025.

21. Drakoulogkonas P, Apostolou D. On the selection of process mining tools. Multidisciplinary Digital Publishing Institute, 2021.

22. Li P. The role of ChatGPT in elevating customer experience and efficiency in automotive after-sales business processes. Multidisciplinary Digital Publishing Institute, 2024.

23. Li Y, Chen MH, Liu Y, et al. An empirical study on the efficacy of deep active learning for image classification, 2022.

24. Lu Y, et al. Human still wins over LLM: An empirical study of active learning on domain-specific annotation tasks, 2023.

25. Duan C, Jia T, Cai H, et al. AFALog: A general augmentation framework for log-based anomaly detection with active learning. IEEE International Symposium on Software Reliability Engineering, 2023.

26. Tsai C, Duraipandi O, Ali DA. Research on risk control and sustainability strategies of AI-driven big data analytics in LEAN manufacturing equipment rCd. Future Technology, 2025.

27. Farmanesh A, Sanchis RG ordieres-Mer J. Comparison of deep transfer learning against contrastive learning in industrial quality applications for heavily unbalanced data scenarios when data augmentation is limited. Italian National Conference on Sensors, 2025.