SILESIAN UNIVERSITY OF TECHNOLOGY PUBLISHING HOUSE

SCIENTIFIC PAPERS OF SILESIAN UNIVERSITY OF TECHNOLOGY 2026
ORGANIZATION AND MANAGEMENT SERIES NO. 245

ARTIFICIAL INTELLIGENCE AS A CATALYST FOR THE REDEFINITION OF PROCESSES IN ORGANIZATIONS

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Purpose: This paper examines how artificial intelligence (AI) redefines the structure and execution of supporting business processes, with a focus on micro-level process changes affecting workflows, roles, and efficiency.
Design/methodology/approach: The study uses a qualitative, exploratory approach combining a literature review with multiple case studies. Two AI implementations were analyzed: Excel translation automation in a financial corporation and AI-driven procurement automation in a commercial organization. The analysis applies process-before/after comparisons using BPMN, pattern matching, and cross-case synthesis.
Findings: AI implementation appears to enable reconfiguration of supporting business processes, including shorter cycle times, simpler process structures, fewer actors, and reduced manual errors. Employee roles shift from execution to supervision and analytical tasks, while process maturity appears to emerge as a key enabler of effective transformation.
Research limitations/implications: The qualitative design and limited number of cases restrict generalizability. Future research should adopt longitudinal designs and include a wider range of industries and process maturity levels.
Practical implications: AI should be implemented as a process transformation initiative rather than isolated automation. Organizations should prioritize mature supporting business processes and invest in analytical and supervisory competencies, achieving improved efficiency, data quality, and scalability.
Social implications: AI adoption reduces routine work and increases demand for knowledge-intensive roles, influencing job design and skill development.
Originality/value: The paper offers a micro-analytical, process-centric perspective on AI-driven transformation of supporting business processes, contributing empirical evidence to BPM and digital transformation research.
Keywords: Artificial intelligence; supporting business processes; business process management; process maturity; dynamic capabilities.
Category of the paper: Literature review; Case study.

1. Introduction

The rapid development of artificial intelligence (AI) has become an important driver of organizational change, affecting not only strategic decision-making but also the execution of business processes (Brynjolfsson, McAfee, 2017). Recent holistic reviews further underline that AI technologies underpin transformations across virtually all sectors, yet empirical evidence on micro‑level process changes remains scarce (Rashid, Kausik, 2024). Within the field of business process management (BPM), AI is increasingly discussed as an enabling technology for automating repetitive tasks, improving information quality, and enhancing workflow coordination.

However, existing research predominantly adopts a macro-level perspective, focusing on strategic or organizational implications of AI adoption, while micro-level evidence on AI-induced process transformation remains limited. This gap is particularly visible in the context of supporting business processes, which, although not directly linked to customer value creation, are critical for organizational stability and are frequently selected as initial candidates for AI implementation.

This study addresses this gap by examining how AI reshapes the structure and execution of supporting business processes and by exploring the associated operational effects and changes in role allocation. Based on a comparative analysis of two supporting business processes in different organizational contexts, the study is guided by the following research questions:

RQ1. What structural changes occur in supporting business processes following AI implementation, particularly in terms of activities, sequencing, and actors?

RQ2. What operational effects are observed in supporting business processes following AI implementation, as reflected in changes to process cycle time, error-prone activities, and information flow?

RQ3. How does AI-driven transformation of supporting business processes alter employee roles and task allocation within the process architecture?

The study aims to explain how AI influences supporting business processes and what these changes imply for process execution, using a comparative case‑based design and BPMN before–after models to capture micro‑level dynamics. It contributes by detailing concrete mechanisms of AI‑enabled change in supporting business processes, focusing on structural, procedural, and role‑related modifications visible in process models and performance metrics, rather than only on firm‑level or sector‑level outcomes.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature on AI, supporting business processes, process maturity, and dynamic capabilities. Section 3 presents the research methodology. Section 4 reports the empirical findings. Section 5 discusses the results in relation to prior research, and Section 6 concludes the paper with implications, limitations, and directions for future research.

2. Theoretical background

2.1. Artificial Intelligence in Business Process Management (AI–BPM)

Artificial intelligence (AI) has become a significant driver of change in business process management (BPM), extending traditional approaches to automation toward intelligent, data-driven process execution and control. Classical BPM and reengineering literature emphasized the transformative role of information technology in eliminating non-value-adding activities and redesigning process structures (Davenport, 1993; Hammer, Champy, 1993; Harmon, 2002). While comprehensive overviews document AI's pervasive role in transforming industries from manufacturing to healthcare and finance (Rashid, Kausik, 2024), far less is known about how these technologies reconfigure specific supporting business processes. Contemporary AI-BPM research builds on this foundation by conceptualizing AI as embedded across the BPM lifecycle, particularly in process execution, monitoring, and decision support (Dumas et al., 2018; Fettke, Di Francescomarino, 2025).

Recent anchor studies highlight that AI contributes not only to task automation but also to process logic reconfiguration, including automated decision points, dynamic routing, and intelligent orchestration of activities (Abbasi et al., 2024; Weinzierl et al., 2024). Explainable and fully automated process redesign approaches demonstrate how AI can reshape end-to-end process structures rather than optimize isolated tasks, supporting a shift from rule-based automation toward adaptive process execution (Weinzierl et al., 2024). Despite these advances, much of the empirical literature remains focused on macro-level outcomes such as productivity or firm performance, leaving micro-level process transformations insufficiently explored (Brynjolfsson, McAfee, 2017; Dwivedi et al., 2021).

From a work perspective, AI–BPM literature consistently points to work augmentation rather than full substitution of human labor. Machine learning systems increasingly perform routine information processing, while human actors transition toward supervisory, analytical, and exception-handling roles embedded within process architectures (Brynjolfsson, Mitchell, 2017; Jarrahi, 2018). Employee perception studies further confirm that smart technologies reshape task allocation and role positioning within processes, reinforcing the relevance of micro-level process analysis (Brougham, Haar, 2018).

2.2. Supporting business processes and Process Maturity

Business processes are commonly classified into operational, supporting, and managerial processes (Davenport, 1993). While operational processes directly create customer value, supporting business processes—such as HR, IT, finance, or logistics—provide critical resources and coordination mechanisms that enable core activities. Although supporting business processes do not generate direct customer value, they are essential for organizational

stability and the effective functioning of operational processes (Dumas et al., 2018; Winiarska, Kizielewicz, 2023).

Due to their standardized structure, repetitive activities, and intensive information processing, supporting business processes are frequently selected as early candidates for AI-enabled automation, including robotic process automation and intelligent document processing (Willcocks et al., 2016). AI–BPM research indicates that the depth of AI-induced transformation is contingent on process maturity, defined as the degree of standardization, documentation, monitoring, and measurement of process execution (Rosemann, vom Brocke, 2010). Focusing on supporting business processes does not imply lower analytical relevance; rather, it enables clearer observation of AI-induced micro-level reconfiguration due to higher standardization and formalization.

Anchor studies emphasize that mature processes provide the transparency and data availability required for embedding AI into process execution logic rather than limiting its use to isolated task automation (Fettke, Di Francescomarino, 2025). Empirical evidence suggests that in high-maturity contexts, AI can facilitate deeper process reconfiguration, including the elimination of non-value-adding activities, reduction of handovers, and tighter integration of information flows across organizational units (Mikalef, Gupta, 2021; Abbasi et al., 2024; Weinzierl et al., 2024). In contrast, low-maturity processes typically experience fragmented automation with limited structural impact. Despite their suitability as an empirical context, supporting business processes remain underrepresented in micro-level AI-BPM research.

2.3. Dynamic Capabilities and Micro-Level Process Change

Dynamic capabilities theory provides a robust lens for interpreting AI-enabled process transformation. Dynamic capabilities refer to an organization's ability to sense opportunities, seize technological potential, and reconfigure operational routines in response to environmental change (Teece, 2018). While early research focused primarily on firm-level and strategic outcomes, more recent studies emphasize the importance of micro-foundations, including business processes through which adaptation is enacted.

From this perspective, AI functions as an enabling mechanism that supports process-level transformation by embedding automated information processing and decision support into existing workflows (Mikalef, Gupta, 2021). Anchor papers explicitly link AI-enabled BPM to dynamic capabilities by demonstrating how intelligent orchestration and process redesign contribute to the reconfiguration of operational routines (Abbasi et al., 2024; Weinzierl et al., 2024).

Micro-level changes, such as simplified process structures, automated information flows, reduced handovers, and redefined human roles, constitute observable manifestations of organizational adaptability. Importantly, AI does not generate dynamic capabilities autonomously; its transformative potential depends on process maturity, clarity of routines, and alignment between technology and human roles (Fettke, Di Francescomarino, 2025).

Due to their context-dependent and process-specific nature, such mechanisms are best examined using qualitative, case-based research designs (Eisenhardt, 1989; Yin, 2018).

3. Methodology

3.1. Research Design and Methods

This study adopts a qualitative, exploratory research design aimed at reconstructing micro-level changes in supporting business processes following AI implementation. The approach is descriptive–analytical and appropriate for research areas where prior empirical evidence remains limited, particularly with regard to AI-induced process transformation at the operational level (Eisenhardt, 1989; Yin, 2018).

To address the research questions, a qualitative multi-method strategy was applied. First, a narrative literature review was conducted as a methodological component to synthesize dominant theoretical perspectives on artificial intelligence in business process management (AI-BPM), supporting business processes, process maturity, and micro-level process change.

The review followed a transparent, theory-oriented search procedure, drawing on peer-reviewed publications indexed in Scopus and Web of Science. The search focused on publications from 2020 to 2025 and employed keywords such as artificial intelligence, business process management, supporting processes, process reconfiguration, and dynamic capabilities. Studies were included if they explicitly addressed AI-enabled process transformation or micro-level changes in organizational processes.

The narrative approach was selected due to the conceptual heterogeneity of the AI-BPM field and the exploratory nature of the study, which makes systematic aggregation of findings inappropriate. Rather than aiming for exhaustiveness, the review focused on identifying conceptually influential and widely cited contributions that informed the theoretical framing and empirical design of the study.

Second, a multiple case study approach was employed to enable in-depth investigation of AI-enabled process transformation in real organizational settings. Following the logic of theoretical replication, cases were selected for their analytical relevance rather than representativeness, allowing for cross-case comparison and analytical generalization (Eisenhardt, 1989; Yin, 2018).

Third, process-level analysis based on BPMN models was used as a core analytical method. Before–after comparison of BPMN representations enabled systematic identification of changes in process structure, task sequencing, automation level, and role allocation following AI implementation. The use of BPMN ensured a consistent analytical language across cases and supported detailed reconstruction of micro-process changes.

The combination of these methods enabled methodological triangulation between theory-oriented synthesis, empirical case analysis, and process modeling, enhancing the robustness and transparency of the research design.

3.2. Data Sources and Data Analysis

Empirical data were collected from two organizations operating in different industry contexts. In each case, the unit of analysis was a single supporting business process examined independently in its pre- and post-AI implementation state. The analyzed processes were characterized by a high degree of formalization, intensive information processing, and substantial human–system interaction.

Case selection followed a purposive sampling strategy based on the following criteria:

1. relevance of the process for organizational support activities,
2. clear potential for AI-enabled automation and process reconfiguration,
3. availability of comparable process documentation before and after AI implementation.

An overview of the studied cases is provided in Table 1.

Table 1.
Studied cases

Case	Organization	Process	AI Technology
A	International financial corporation	Excel file translation	NLP + workflow automation
B	Large retail organization	Purchasing process	AI-driven demand forecasting + OCR/NLP

Source: own elaboration.

Data sources included operational documentation, process architecture descriptions, and BPMN process models depicting process execution before and after AI implementation. Additional process-related indicators were derived from organizational records and expert validation, including indicative process cycle times, number of process steps, number of involved actors, and main sources of manual errors. Where system logs were incomplete, expert estimates provided by process owners were used to complement available data; therefore, some reported values should be interpreted as indicative rather than statistically representative.

Data analysis followed a three-stage procedure. First, before–after process comparison was conducted using BPMN models to identify changes in task structure, sequencing, automation level, and role allocation. Second, within-case analysis was performed to document process-level changes separately for each organization. Third, cross-case synthesis was applied to identify recurring patterns of AI-induced transformation across both cases.

The analysis focused on observable structural, procedural, and role-related changes in supporting business processes. Quantitative indicators, such as cycle time reduction or reduction in actor involvement, were used to illustrate the magnitude of observed changes, while the primary emphasis remained on qualitative reconstruction of process execution logic.

The interpretation of findings in relation to BPM and dynamic capabilities literature is presented in the Discussion section.

4. Empirical Findings

4.1. Case A – Automation of Excel Translation in a Financial Corporation

Case A (Appendix, Figure 1) concerns a large financial corporation collaborating extensively with clients in the Asia-Pacific region. Translating Excel files (between Asian languages and English) was critical for operational information flow, as files contained both descriptive content and complex formulas that needed to be preserved. Delays in this process impeded timely client responses and subsequent analytical work. Process Steps Before and After AI Implementation are presented in Table 2.

Before AI implementation, translation was entirely manual, performed by internal and external translators. Files were repeatedly passed between units, increasing the risk of formatting errors and content inconsistencies. Average processing time per file was 2-3 days, with low standardization of work.

The solution implemented Alteryx Designer with Intelligence Suite, automating data flows and applying AI for content extraction and processing. Key functionalities included:

- OCR and text extraction from files (Image/PDF to Text module).
- Content analysis and classification via text mining.
- Automated processing, structuring, and transformation using rule-based workflows and Python scripts.
- Terminology unification and content generation through Generative AI integrated with language models.

Table 2.
Case A – Process Steps Before and After AI Implementation

Step	Pre-AI (Manual)	Post-AI (Automated)	Key AI Value
1	File receipt & registration	Automatic file capture by workflow	Eliminates manual handover
2	Manual scope analysis	Automatic structure & metadata extraction	Speed & completeness
3	Manual translation	NLP translation with glossaries	Terminology consistency
4	Manual formula reconstruction	Automatic formula mapping	Error-free references
5	Manual formatting correction	Automatic content & format merge	Maintains layout
6	Verification by another employee	Automatic validation + exception routing	Reduces human effort
7	Business testing & adjustments	QA only for exceptions	Eliminates iterative cycles
8	Finalization & distribution	Automatic publishing & logging	Full auditability & speed

Source: own elaboration.

The automated workflow eliminated manual copying, reduced errors, and drastically shortened processing time. Human roles shifted from execution to oversight of data quality. Post-implementation, the average file translation took only a few minutes. The process became scalable, reliable, and focused on control and interpretation rather than manual operation.

4.2. Case B – AI in Purchasing Process Automation in a Retail Organization

Case B (Appendix, Figure 2) analyzed a purchasing process in a large retail organization, where timely ordering is critical for product availability and cost optimization. Prior to AI, purchasing required extensive manual work: employees monitored inventory and sales data, created orders, and entered information into ERP systems. Process Steps Before and After AI Implementation are presented in Table 3. Logistics and financial documents were handled separately, risking delays and errors.

AI implementation included predictive algorithms analyzing sales history and demand seasonality, combined with automatic document recognition for real-time classification and data entry. Key AI components:

- OCR for data extraction from purchase documents (orders, delivery notes, invoices).
- NLP for field recognition, document classification, and content validation.
- Demand forecasting model generating orders automatically.
- Automated document matching linking orders, invoices, and delivery notes.
- Workflow orchestration and API integration enabling automatic information flow between the purchasing system and suppliers.

Table 3.
Case B – Process Steps Before and After AI Implementation

Step	Pre-AI (Manual)	Post-AI (Automated)	Key AI Value
1	Manual request reporting	AI proactive alerts	Eliminates response delays
2	Manual demand forecasting	Automatic prediction	Accurate forecasts, no Excel sheets
3	Manual order creation	Automated order generation	Reduces errors & time
4	Manual dispatch & confirmation	API integration, real-time status	Process transparency
5	Manual data entry from documents	OCR + NLP automated extraction	Eliminates transcription errors
6	Manual document matching	Automated matching (order–invoice–delivery)	Faster reconciliation
7	Frequent exception handling	Human only for exceptions	Reduces escalations
8	Process closure & posting	Automatic audit & reporting	Shortened reconciliation time

Source: own elaboration.

Manual tasks were substantially reduced, shortening process duration by 60-80%. Employees transitioned to exception handling and system oversight, enabling data-driven decisions and enhancing organizational adaptive capacity.

5. Results

The empirical analysis followed a three-stage procedure: (1) before–after comparison of process models, (2) identification of recurring patterns across cases, and (3) cross-case synthesis. This section reports the observed changes in supporting business processes following AI implementation, without extending into theoretical interpretation.

Table 4 presents a comparative overview of key process metrics before and after AI implementation in both cases.

Table 4.
Comparison of Key Process Metrics Before and After AI Implementation

Metric	Case A – Excel Translation	Case B – Purchasing	Observed Process-Level Effect
Cycle time	2-3 days → 5-10 minutes (approx. –95–98%)	3-7 days → < 1 hour (approx. –95–98%)	Elimination of waiting time and manual coordination
Process structure	8 → 6 steps (–25%)	8 → 6 steps (-25%)	Reduction of non-value-adding activities and handovers
Actor involvement	3 → 1 actor	6 → 1 actor	Centralization of execution with distributed supervision
Error exposure	Manual translation → automated NLP	Manual entry → automated validation	Shift from human error-prone tasks to system-level controls
Human role	Operational execution → supervision and analytics	Manual input → exception handling and oversight	Reallocation of human effort toward higher-level activities

Source: own elaboration.

The empirical analysis shows observable changes in both operational performance indicators and the structure execution logic of the analyzed supporting processes. Across both cases, AI-enabled automation reduced structural complexity by eliminating manual tasks and consolidating execution roles. Process flows became more compact, with fewer handovers and reduced exposure to delay- and error-prone activities.

Before–after analysis of BPMN models further revealed systematic changes in role allocation. Tasks previously performed manually—such as data entry, translation, and document verification—were automated, while human involvement shifted toward supervision, exception handling, and validation. In parallel, information handling within the processes changed through the reduction of data duplication and transcription points and increased consistency of information flows.

Despite differences in organizational context and process type, cross-case synthesis revealed recurring patterns of AI-induced transformation. Both cases exhibited simplified process structures, increased system autonomy in routine execution, and implementation within standardized and formally documented supporting processes. These recurring patterns were observed across both cases at the micro-process level.

The observed effects of AI implementation can be grouped into three interrelated empirical dimensions: **structural effects**, reflected in simplified process design and reduced actor involvement; **procedural effects**, manifested in shorter process cycles and reduced exposure to manual errors; and **role-related effects**, involving the reallocation of human effort toward supervision, exception handling, and analytical activities.

Together, these findings provide empirically grounded answers to the research questions, summarized in Table 5.

Table 5.
Research Questions, Findings, and Implications

RQ	Finding	Theoretical Implication	Practical Implication
RQ1	Process reconfiguration rather than isolated automation	AI contributes to changes in operational logic	Design AI deployment as a process transformation initiative
RQ2	Simplified process structure, fewer error-prone activities, improved resilience	AI strengthens process-level capabilities	Prioritize standardized and mature processes for AI deployment
RQ3	Shift toward supervisory and analytical roles	Supports the concept of work augmentation	Invest in process, digital, and analytical skills

Source: own elaboration.

The interpretation of these findings in relation to BPM and dynamic capabilities literature is presented in the Discussion section.

6. Discussion

The findings show that artificial intelligence reshapes supporting business processes not only through task automation but through structural and logical process reconfiguration.

The empirical results reported in the Results section document observable micro-level changes in process structure, execution logic, and role allocation, without implying any direct measurement of organizational capabilities.

The observed micro-level changes can be interpreted as process-level manifestations of broader AI-driven industrial transformation described in the Industry 4.0/5.0 literature (Rashid, Kausik, 2024).

The conceptual model presented in Figure 3 specifies three micro-level dimensions of change—process logic, data handling, and role transformation—and links them to process maturity in supporting business processes. The model synthesizes recurring empirical patterns identified across the analyzed cases, including fewer handovers, centralized execution with distributed supervision, and a shift toward AI-supported exception handling in back-office contexts.

In both cases, AI implementation led to simplified workflows, shorter execution cycles, and performance gains stemming primarily from process redesign consistent with core BPM principles. These effects were observed at the level of process structure and execution and are summarized in Table 6, which synthesizes the micro-level effects of AI implementation in supporting business processes.

Table 6.
Micro-Level Effects of AI Implementation in Supporting Business Processes

Change Dimension	AI Implementation Effects
Structural	Fewer process steps and actors; streamlined workflows
Procedural	Shorter operational cycles; reduced exposure to manual errors
Competency	Shift toward supervision and analytical activities; increased process oversight

Source: own elaboration.

These results are consistent with classical BPM redesign principles (Davenport, 1993; Hammer, Champy, 1993) and extend them into an AI-enabled context. Rather than radical reengineering, the cases illustrate incremental yet deep reconfiguration embedded within existing process structures, supporting recent AI-BPM research that emphasizes intelligent orchestration over isolated automation (Fettke, Di Francescomarino, 2025).

Process maturity emerged as a key boundary condition for AI-driven transformation. The empirical cases indicate that standardized and well-documented supporting business processes provide favorable conditions for embedding AI at the level of process logic, reinforcing BPM maturity frameworks (Rosemann, vom Brocke, 2010) and research on AI capability development (Mikalef, Gupta, 2021).

AI implementation also altered human involvement in supporting business processes. Consistent with the augmentation-of-work perspective (Brynjolfsson, Mitchell, 2017; Jarrahi, 2018), employee roles shifted toward supervision and analytical activities. Importantly, these role changes emerged as consequences of process redesign rather than as outcomes of explicit human resource interventions, aligning with prior research on technology-induced role transformation (Brougham, Haar, 2018).

From a dynamic capabilities perspective, the observed process transformations can be interpreted as micro-level manifestations of organizational adaptability. However, it should be emphasized that dynamic capabilities are not directly measured in this study and are employed solely as an interpretative lens to contextualize the observed process-level changes, rather than as constructs subjected to theory testing (Teece, 2018).

The integration of structural, procedural, and role-related changes is synthesized in the conceptual model of AI-enabled supporting business process transformation (Figure 3). The model serves as an analytical framework that explains how AI-enabled reconfiguration may emerge under conditions of sufficient process maturity, rather than as a prescriptive or universally generalizable solution.

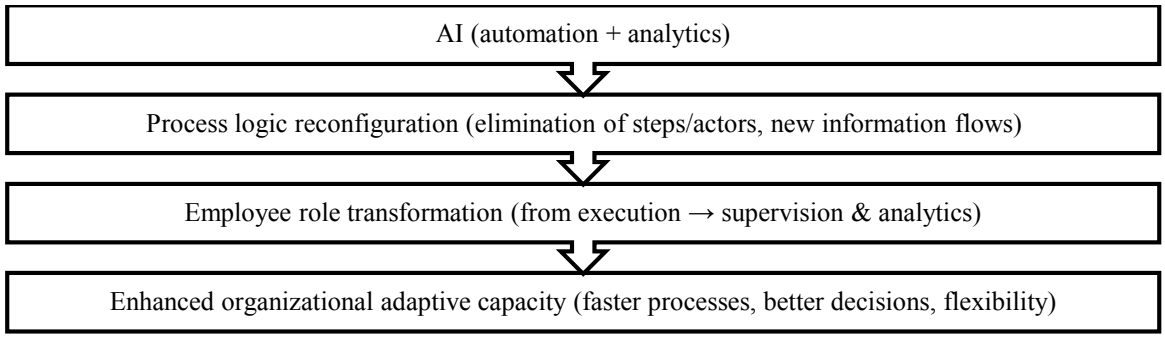

Figure 3. Model of Supporting Business Process Transformation through AI.

Source: own elaboration.

The model is specifically tailored to supporting business processes, where high standardization, intensive information processing, and multi-actor coordination make reductions in handovers and actor involvement particularly visible indicators of AI-enabled reconfiguration.

Overall, this study contributes to AI–BPM research by shifting the analytical focus from isolated task automation to micro-level process reconfiguration in supporting business processes, providing empirically grounded insights into how AI reshapes process execution logic and work organization.

7. Conclusions and Contributions

7.1. Overall Conclusions

This study examined the impact of artificial intelligence on supporting business processes from a micro-process perspective using a qualitative, case-based research design. The findings demonstrate that AI implementation is associated with changes not only in operational efficiency but also in process structure, execution logic, and role allocation. Across the analyzed cases, AI-enabled solutions contributed to simplified process flows, reduced reliance on manual coordination, and a shift of human work toward supervisory and analytical activities. The results further indicate that process maturity plays an important contextual role in shaping the scope and effectiveness of AI-driven transformation. Overall, the study contributes to the business process management literature by providing micro-level, empirically grounded evidence on how artificial intelligence reshapes supporting business processes beyond isolated task automation.

7.2. Practical Implication

For practitioners, the findings suggest that AI initiatives in supporting business processes should be approached as process transformation projects rather than isolated automation efforts. Organizations are likely to benefit most from deploying AI in processes that are already standardized, transparent, and measurable. Additionally, managerial attention should be directed toward redesigning roles and governance mechanisms to support increased system autonomy and effective human oversight.

7.3. Study Limitations

This study has several limitations. First, it is based on two case studies, which constrains the generalizability of the findings. Second, the observation period was relatively short, limiting insights into long-term effects, particularly with respect to organizational learning and cultural change. Third, conclusions regarding employee competencies are based on inferred role changes rather than direct empirical measurement. As a result, conclusions regarding role and competency changes should be interpreted as inferences from process models and performance data rather than from self‑reported experiences.

7.4. Future Research Directions

Future research could address these limitations by adopting longitudinal designs, incorporating interviews or ethnographic methods to examine competency development, and comparing different types of AI technologies across varying levels of process maturity. Further investigation into less formalized supporting business processes may also enhance understanding of the boundaries of AI-enabled process transformation.

References

1. Abbasi, M., Nishat, R.I., Bond, C., Graham-Knight, J.B., Lasserre, P., Lucet, Y., Najjaran, H. (2024). A review of AI and machine learning contribution in business process management (process enhancement and process improvement approaches). *Business Process Management Journal*, *Vol. 31, Iss. 4*, pp. 1414-1452. https://doi.org/10.1108/bpmj-07-2024-0555
2. Brougham, D., Haar, J. (2018). Smart technology, artificial intelligence, robotics, and algorithms (STARA): Employees' perceptions of our future workplace. *Journal of Management & Organization, 24(2)*, 239-257. https://doi.org/10.1017/jmo.2016.55
3. Brynjolfsson, E., McAfee, A. (2017). *Machine, platform, crowd: Harnessing our digital future*. W.W. Norton & Company.

4. Brynjolfsson, E., Mitchell, T. (2017). What can machine learning do? Workforce implications. *Science, 358(6370)*, 1530-1534. https://doi.org/10.1126/science.aap8062
5. Davenport, T.H. (1993). *Process innovation: Reengineering work through information technology*. Harvard Business School Press.
6. Dumas, M., La Rosa, M., Mendling, J., Reijers, H.A. (2018). *Fundamentals of business process management*. Springer.
7. Dwivedi, Y.K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P.V., Janssen, M., Jones, P., Kar, A.K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., Medaglia, R., Le Meunier-FitzHugh, K., Misra, S., Mogaji, E., Sharma, S.K., Singh, J.B., Raghavan, V., Rana, N.P., Samothrakis, S., Spencer, J., Tamilmani, K., Tubadji, A., Walton, P., Williams, M.D. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management, 57, 101994.* https://doi.org/10.1016/j.ijinfomgt.2019.08.002
8. Eisenhardt, K.M. (1989). Building theories from case study research. *Academy of Management Review, 14(4)*, 532-550. https://doi.org/10.5465/amr.1989.4308385
9. Fettke, P., Di Francescomarino, C. (2025). Business Process Management and Artificial Intelligence. *Künstl Intell, 39*, 67-79. https://doi.org/10.1007/s13218-025-00891-y
10. Hammer, M., Champy, J. (1993). *Reengineering the corporation: A manifesto for business revolution*. Harper Business.
11. Harmon, P. (2002). *Business process change: A manager's guide to improving, redesigning, and automating processes*. Morgan Kaufmann.
12. Jarrahi, M.H. (2018). Artificial intelligence and the future of work: Human–AI symbiosis in organizational decision making. *Business Horizons, 61(4)*, 577-586. https://doi.org/10.1016/j.bushor.2018.03.007
13. Mikalef, P., Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management, 58(3), 103434.* https://doi.org/10.1016/j.im.2021.103434
14. Rashid, A.B., Kausik, M.A.K. (2024). AI revolutionizing industries worldwide: A comprehensive overview of its diverse applications. *Hybrid Advances, 7,* 100277. https://doi.org/10.1016/j.hybadv.2024.100277
15. Rosemann, M., vom Brocke, J. (2010). The six core elements of business process management. In: J. vom Brocke, M. Rosemann (Eds.), *Handbook on business process management, 1* (pp. 107-122). Springer. https://doi.org/10.1007/978-3-642-00416-2_5
16. Teece, D.J. (2018). Business models and dynamic capabilities. *Long Range Planning, 51(1)*, 40-49. https://doi.org/10.1016/j.lrp.2017.06.007

17. Weinzierl, S., Zilker, S., Dunzer, S., Matzner, M. (2024). Machine learning in business process management: A systematic literature review. *Expert Systems with Applications, Vol. 253, 124181*. https://doi.org/10.1016/j.eswa.2024.124181
18. Willcocks, L.P., Lacity, M.C., Craig, A. (2016). Robotic process automation: The next transformation lever for shared services. *The Outsourcing Unit Working Research Paper Series, 16/01*. Retrieved from: https://www.umsl.edu/~lacitym/OUWP1601.pdf, 28.12.2025.
19. Winiarska, M., Kizielewicz, J. (2023). Process management in organizations: A discussion on terminology. *Management, 27(1)*, 20-54. https://doi.org/10.58691/man/168612
20. Yin, R.K. (2018). *Case study research and applications: Design and methods (6th ed.)*. Sage.

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Appendix

BPMN models of case studies

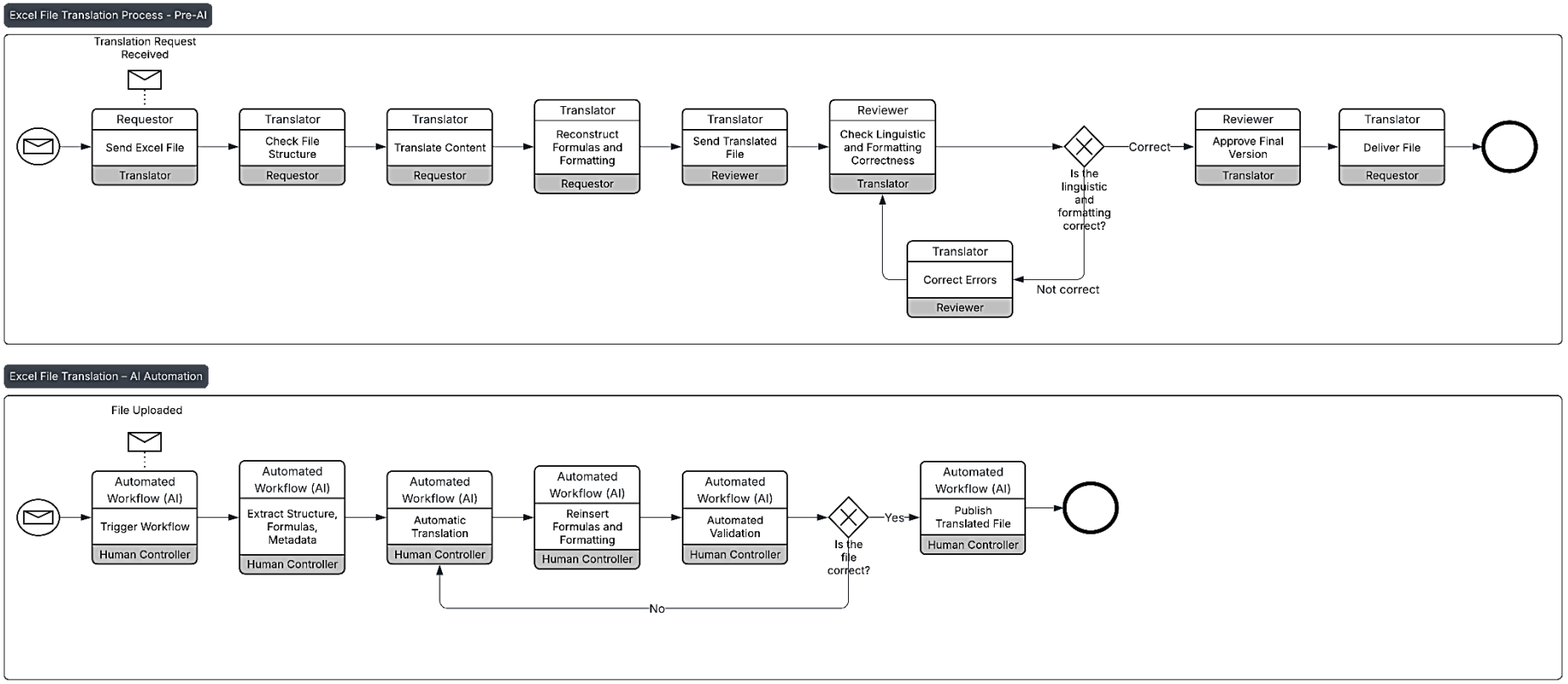

Figure 1. BPMN model of supporting business process A before and after AI implementation.

Source: own elaboration.

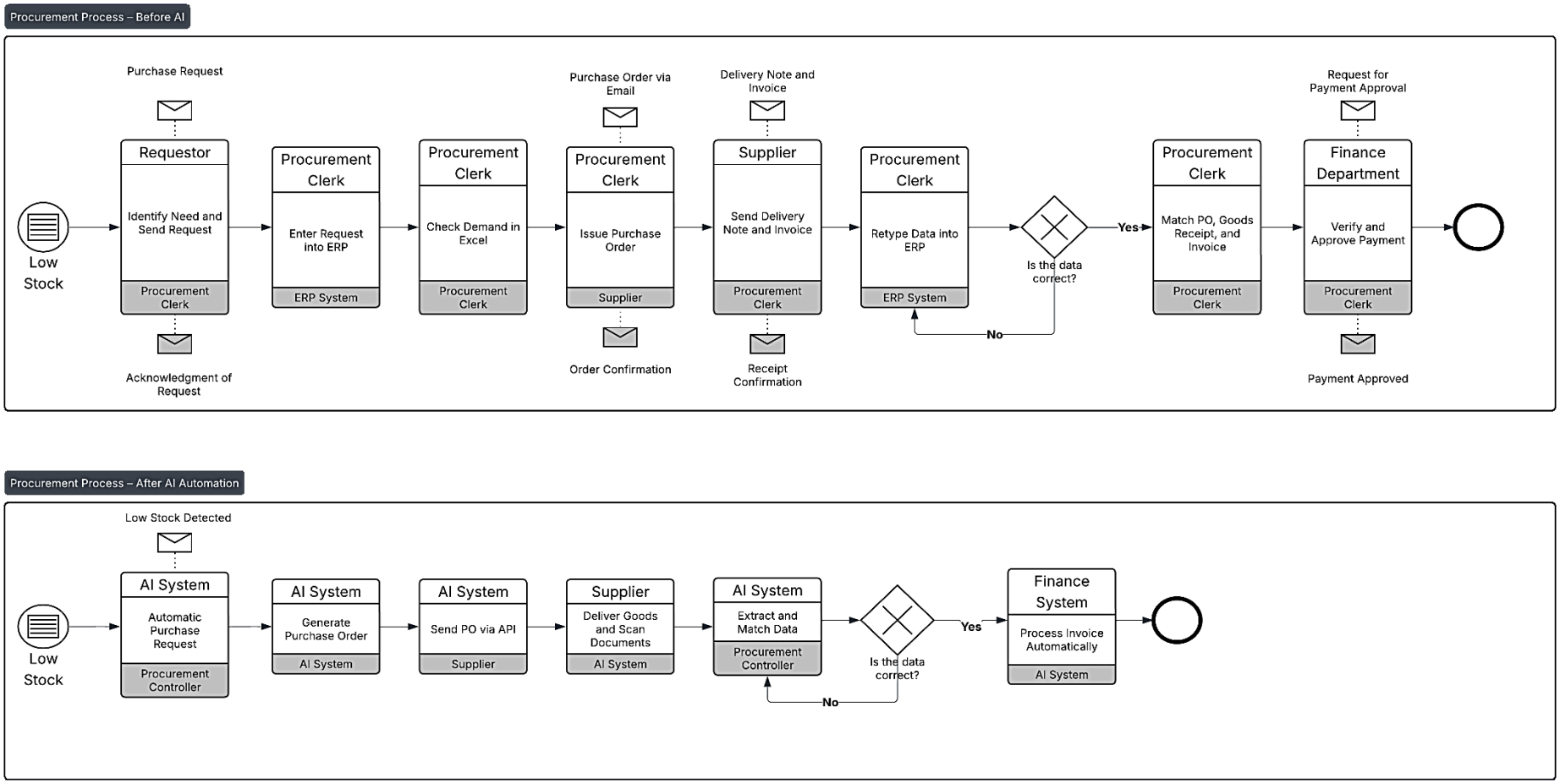

Figure 2. BPMN model of supporting business process B before and after AI implementation.

Source: own elaboration.