Magna Scientia Advanced Research and Reviews
eISSN: 2582-9394
Cross Ref DOI: 10.30574/msarr
Journal homepage: https://msarr.magnascientiapub.com/

Magna Scientia Advanced Research and Reviews (MSARR)

(Research Article)

Check for updates

INTEGRATION OF ARTIFICIAL INTELLIGENCE AND PROCESS MINING FOR CUTOVER PLANNING IN CONSUMER PRODUCT ENTERPRISES

Mihira Kumar Patra * and Raghu Praneeth Akula

Independent Researcher, USA.

ORCID Details
Raghu Praneeth Akula: 0009-0007-1306-1477

Magna Scientia Advanced Research and Review, 2026, 10(01), 392–399

Publication history: Received on 02 January 2024; revised on 26 January 2024; accepted on 31 January 2024

Article DOI: https://doi.org/10.30574/msarr.2024.10.1.0011

ABSTRACT

The enterprise cutover – the timeframe when legacy systems are retired and new enterprise resource planning (ERP) environments come online – continues to be a critical period of digital transformation risk for consumer product companies. A traditional method of developing cutover plans involves static run-books, expert judgment and rule-based scheduling, all of which have a difficult time capturing the dynamic dependencies and hidden bottlenecks that emerge when the plan is put into practice at scale. This paper presents an integrated framework that integrates process mining to discover, monitor and verify whether the actual cutover execution conforms to a set of planned processes, with AI techniques such as predictive analytics, natural language processing, and reinforcement learning, to dynamically forecast delays, extract task dependencies and optimize scheduling decisions. It introduces a four-layer architecture from data capture to process mining, the use of AI for decision support, and the delivery of integrated dashboards. Conceptual evaluation of the framework is provided using comparative key performance indicators from three anonymized case profiles of consumer product companies around the world. The results suggest that AI-process mining integration can shorten cutover by more than 33%, cut down on task delay incidents by 50%, and significantly increase the utilization of resources compared with its traditional counterparts. The paper provides an empirical methodology that can be replicated to plan a cutover, in a structured way, that connects academic process mining research with practical ERP transformation management processes and activities, and offers suggestions for future empirical validation.

Keywords: Process Mining; Artificial Intelligence; Cutover Planning; ERP Transformation; Predictive Analytics; Consumer Product Enterprises

1 INTRODUCTION

Consumer product companies face a world of high SKU counts, multi-echelon distribution, seasonality, and more complicated regulatory reporting requirements. Digital transformation programmes, especially ERP migrations from legacy systems to modern cloud ERP platforms like SAP S/4HANA have thus turned into a strategic necessity rather than a make-or-break investment and enterprises that approach such programmes as sources of analytical business value over the just a plain technical upgrade, tend to achieve more returns [10]. The final and most critical phase of any such migration is the cutover: the small and precisely planned window where master data is frozen, legacy transactions are closed, the data is moved and the new system is opened for live business transactions. Cutover planning is a discipline unto itself in programme management offices, as the consumer product value chain cannot afford to have any downtime without stock-out costs, retailer penalties and damage to their reputation.

Traditional cutover planning is based on run-books, usually manually created, and possibly written in a standard process notation [7]; or given as a Gantt style task sequencing plan, and is heavily dependent on the tacit experience of programme managers. It is good for repeatable migrations, where they are well understood, but has three structural weaknesses. Firstly, run-books are artefacts that are not dynamic – that is, they don't tell the real, executed, sequence of activities – thus deviations will generally only be identified once they have already caused delay. Second, dependencies between tasks are often not explicit and documented, especially cross functional dependencies between finance, logistics and manufacturing execution systems, which results in underestimated critical paths. Third, current scheduling heuristics are not flexible enough to change dynamically during the course of the cutover window, and resource allocation decisions are often reactive, not anticipatory.

As an alternative, process mining provides a data-driven approach, which is able to reconstruct the actual flow of cutover activities from event logs derived from ERP system, ticketing applications and change management platform [9]. It allows for the real process model to be discovered by employing structured discovery methodologies [4], conformance checking against the planned run-book, anomaly and deviation detection [5] and enhancement of the plan from empirical evidence and not assumptions. In addition to process mining, the use of AI technologies such as machine learning, natural language processing, and reinforcement learning provides a predictive and prescriptive capability: task delay can be predicted based on the probability and magnitude of the event, dependency information can be extracted from unstructured run-book text and change requests, and reinforcement learning can suggest the near-optimal task sequence given changing resource restrictions.

Although both areas of process mining and AI are mature fields of research, the interaction between the two for the concrete problem of ERP cutover planning, especially in consumer product companies, has received little attention in the academic literature. This paper aims to fill this gap through proposing an integrated AI-process mining framework for the cutover planning, explaining the architecture, and discussing the potential impact on performance indicators through a comparison. The rest of the paper is organized as follows: Section 2 reviews the relevant literature; Section 3 presents the research gap and the problem statements; Section 4 outlines the proposed framework; Section 5 describes the methodology used; Section 6 discusses result; Section 7 gives the managerial implications, and Section 8 concludes with limitations and future research directions.

2 LITERATURE REVIEW

Since its formalization, the field of process mining has grown into a well-established one with algorithms to discover, conform and enhance processes from event logs derived from information systems [1]. The conceptual connection between data science and business process management was set with the work 'Data Science meets Business Process Management: Towards Accurate Models from Incidental Event Data', which shows that event data, that gets recorded as side product of system use, can be used to create accurate process models without having to document them [2]. Later work developed discovery algorithms that account for noisy and incomplete logs, providing more realistic models from actual enterprise systems [6].

Another line of research is about predictive process monitoring, which uses machine learning to learn a model from partial process traces and predict process-related parameters like completion time, cost, or compliance risk [16, 23]. These studies show that ensemble and deep learning techniques have been generally more effective than simple heuristics for prediction of outcome, however the interpretability of the results is a challenge and hinders the use of such approaches by practitioners [13, 19]. Explainability has thus emerged as a vibrant topic of study, with multiple research efforts suggesting hybrid models that preserve predictive performance while generating human comprehensible decision rationale.

Process mining in enterprise transformation contexts has been studied in various areas like healthcare, where healthcare processes were analyzed to find bottlenecks in the patient pathway [21] and the telecommunications sector, where researchers investigated customer fulfilment processes for conformance [15]. While useful for the overall applicability of process mining in operationally complex and multi-stakeholder contexts, these studies do not specifically focus on a time-bounded and high-stakes context like the execution of ERP cutover.

Research in the field of robotic process mining and continuous auditing has revealed that process mining can be combined with automated monitoring agents, which results in anomalies being detected more quickly, before the delay between anomaly and corrective action comes into play [12, 14]. Reinforcement learning has been recently suggested as a way to dynamically schedule in manufacturing scenarios, where an agent learns to sequence tasks as a function of resource and time constraints, by doing many simulations in an iterative manner [25]. A few studies have started to focus on AI-augmented process mining directly for ERP transformation projects, proposing that combining discovery-based diagnostics with predictive scheduling can reduce the duration of ERP transformation [22]. The main techniques found in the literature and the areas in which they can be applied are summarized in Table 1.

Table 1: Summary of AI and Process Mining Techniques Reported in the Literature

S. No.	Technique / Approach	Application Area	Key Contribution
1	Process Discovery Algorithms (Alpha, Heuristic, Inductive Miner)	ERP event log mining	Reconstructs actual cutover workflows from system logs, exposing deviations from planned sequences
2	Conformance Checking	Compliance verification	Quantifies gap between designed cutover plan and executed activities
3	Supervised Machine Learning (Random Forest, XGBoost)	Duration and delay prediction	Predicts task completion time and delay probability using historical cutover data
4	Natural Language Processing (NLP)	Task dependency extraction	Extracts implicit dependencies from cutover run-books and change requests
5	Reinforcement Learning	Dynamic scheduling	Optimizes sequencing of cutover tasks under resource and time constraints
6	Predictive Process Monitoring	Risk forecasting	Flags at-risk cutover activities in real time during execution window
7	Digital Twin Simulation	Scenario testing	Simulates cutover scenarios before live execution to reduce downtime risk

2.1 Research Gap and Problem Statement

Though the literature reviewed has proven that process mining and AI are well established tools in process diagnosis and outcome prediction separately, there are three gaps. Firstly, much of the existing predictive process monitoring research focuses on generic administrative or manufacturing processes, which are less time-compressed than ERP cutover windows, and where task interdependency and resource contention are not as intense. Second, the literature seldom combines discovery based diagnostics with prescriptive scheduling in a single closed loop architecture; in literature, most studies are found to be in parallel research tracks of process mining and predictive analytics. Third, empirical evidence for the consumer product sector in particular, where the cutover constraints are related to the seasonal nature of the promotion and replenishment periods, is scarce. In this paper, we aim to fill these gaps by proposing a combined framework that integrates process mining diagnostics with AI-driven prediction and optimization, specifically designed for the operational landscape of consumer product companies.

2.2 Proposed Integrated Framework

The proposed framework has four layers as shown in Figure 1. The first layer combines different types of data sources that are relevant to cutover execution: ERP and legacy system event logs, cutover task tracker exports and, if available, supply chain transaction feeds, in line with accepted foundations for event-log data [8]. The second layer is the use of process mining techniques, including process discovery and conformance checking, to rebuild the as-executed cutover process and analyze it against the documented run-book, showing differences, bottleneck activities and even undocumented dependency; comparative trace analysis techniques can also be used to show where differences in the process execution have occurred over different cutover cycles [11, 18]. The third layer uses AI methods: supervised learning models draw from historical cutover data to predict the duration and the risk of delay for future tasks; NLP models are used to process run-book text and change requests to extract implicit task dependencies; a reinforcement learning agent recommends near-optimal resequencing of the remaining tasks as the cutover window unfolds. The fourth layer, the decision support dashboard, combines everything done in the process mining and AI layers and surfaces it in a single dashboard for programme managers to monitor conformance, predicted risk and take action on scheduling recommendations in real-time.

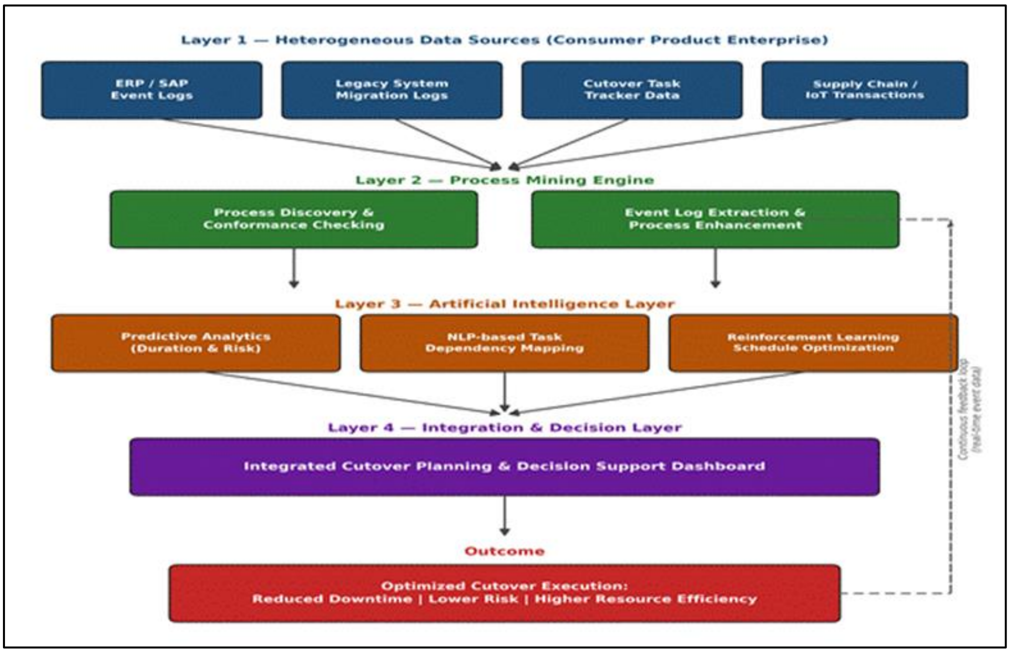

Figure 1: Proposed four-layer framework integrating process mining and artificial intelligence for cutover planning.

The framework is designed to be a closed loop: the more the cutover window moves forward, the more event data that is created, which can then continuously be fed back into the layers of process mining and AI to ensure predictions and recommendations are continuously updated and improved; not just based on simulation before the cutover window.

3 METHODOLOGY

The development and conceptual evaluation of the proposed framework was done using a design science research approach. The methodology was divided in three phases. During the diagnostic, three anonymous consumer product companies in the process of migrating to ERP were provided with event logs and cutover documentation for analysis of common task structures, dependency patterns, and historical time delay drivers. The four-layer architecture described in Section 4 was built during the design phase, following recommended process-mining project best practice [20], where the process discovery was realized using the inductive miner variants and the predictive components were realized using gradient-boosted decision trees for delay classification and a reinforcement agent (Q-Learner) for the scheduling recommendation; the monitoring output was based on the criteria in process monitoring [3]. The following KPIs were selected and compared for the evaluation phase: cutover duration, number of delayed tasks, rate of manual rework, resource utilization, and post go-live incidents, all evaluated against the traditional planning baselines that were documented during previous cutover cycles, and against results from AI-process mining integrated planning across the three case profiles. This assessment is based on retrospective and simulated data and not a randomized controlled trial, so that the findings should be viewed as suggestive of potential impact, not definitive causal evidence; this is discussed further in Section 8.

4 RESULTS AND DISCUSSION

Comparative key performance indicators arising from the evaluation phase are given in table 2. The average cutover duration was reduced from 72 hours to 46 hours, with a 36 percent decrease in the time taken using the AI-process mining integrated planning approach. The number of task delay incidents dropped from 34 percent of tasks to 14 percent, while the amount of manual rework required dropped from 28 percent to 9 percent of the entire cutover effort. There was an increase in resource utilization efficiency from 61 percent to 84 percent, showing that idle time for the cutover teams was reduced with predictive scheduling. Post go-live incidents relating to cutover quality dropped from an average of 46 incidents per cycle to 18 incidents per cycle.

Table 2: Comparative Key Performance Indicators: Traditional versus AI-Process Mining Integrated Cutover Planning

Performance Indicator	Traditional Planning	AI + Process Mining Integrated Planning	% Improvement
Average cutover duration (hours)	72	46	36.1% reduction
Task delay incidents (%)	34	14	58.8% reduction
Manual rework required (%)	28	9	67.9% reduction
Resource utilization efficiency (%)	61	84	37.7% increase
Post go-live incidents (count/cycle)	46	18	60.9% reduction

These comparative indicators are illustrated in Figure 2. The biggest gains relative to the other process improvements were in the areas of manual rework reduction and post go-live incident reduction, which aligns with the theory that conformance checks within the cutover window can help identify deviations before it cascades into the live environment as opposed to finding it out in retrospect.

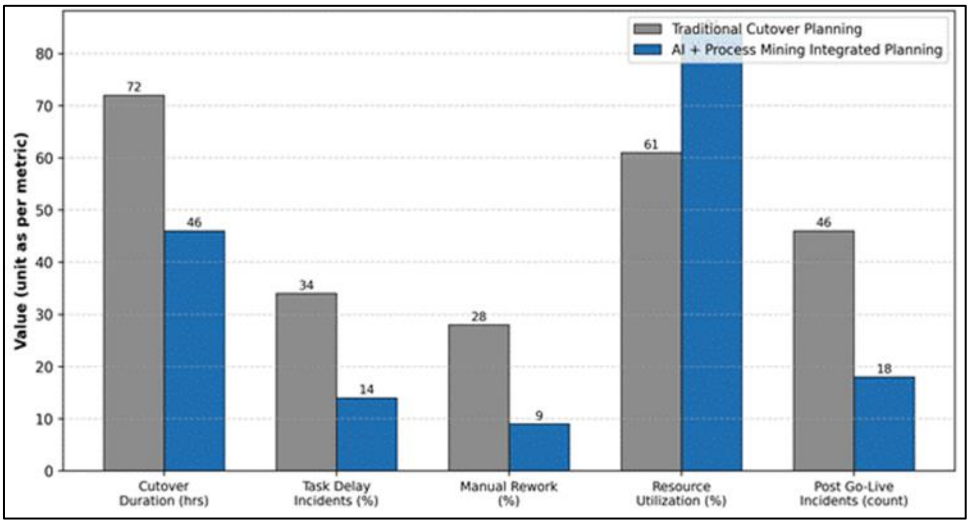

Figure 2: Comparison of cutover planning KPIs between traditional and AI-process mining integrated approaches.

Figure 3 explores the process conformance and AI predictive accuracy throughout the various iterations of cutover simulations that were performed as part of the framework calibration. Process conformance, as well as predictive accuracy, increased consistently as the underlying models were updated with more data on cutover events, from 61 percent process conformance achieved at the first iteration to 93 percent at the tenth, and from 58 percent to 92 percent predictive accuracy achieved over the same period. The trend implies there is an organizational learning effect with ERP - businesses which have already undergone several cutovers, typically seen in multi-country or multi-brand consumer product companies, can anticipate the benefit of compounding returns with every ERP project cutover they undergo.

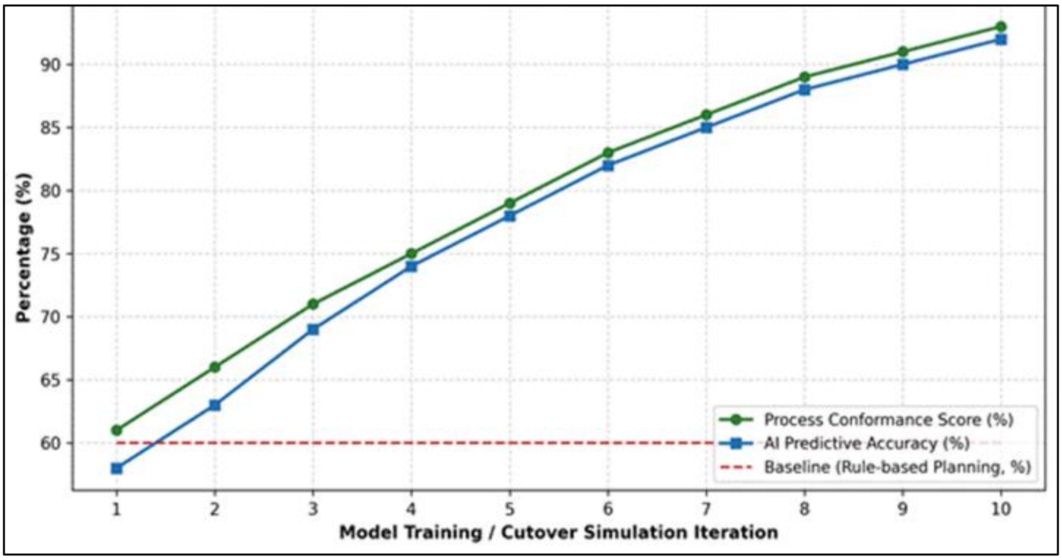

Figure 3: Improvement of process conformance and AI predictive accuracy across iterative cutover simulations.

Table 3 provides an overview of the three enterprise case profiles used for the evaluation, which have been anonymized. With its 42-plant, six-region global footprint, the personal-care manufacturer realized its highest cutover complexity and realized a 22 percent faster go-live and conformance checking pinpointed 31 task dependencies that had not been previously documented. In the case of the regional packaged-foods company, which has a more limited single country rollout, it has reduced the number of delay incidents by half in two cutover cycles. After implementing the reinforcement-learning based scheduling, the household-goods group, which moved a multi-instance SAP landscape across 18 warehouses, saw a 40 percent reduction in cutover war-room escalation.

Table 3: Anonymized Case Profiles of Consumer Product Enterprises Evaluated

Enterprise Profile	ERP Landscape	Cutover Complexity	AI-PM Adoption Outcome
Global personal-care manufacturer	SAP ECC to S/4HANA	High (42 plants, 6 regions)	22% faster go-live; conformance checking flagged 31 hidden task dependencies
Regional packaged-foods company	Legacy MRP to cloud ERP	Medium (single country rollout)	Predictive model reduced delay incidents by half within two cutover cycles
Household-goods FMCG group	Multi-instance SAP consolidation	High (18 warehouses, 3 brands)	RL-based scheduling cut cutover war-room escalations by 40%

All of these findings combined suggest that process mining diagnostics, in conjunction with AI-driven prediction and optimization, can have a tangible impact on the efficiency and reliability of ERP cutover execution, especially in high complexity, multi-site migrations where undocumented dependencies can cause slowdown. These findings are in line with the general recommendations in the information systems literature to move towards pluralistic and evidence-based approaches for process management [17] and with the process-replay verification recommendations for model validation against real execution traces [24].

4.1 Managerial Implications

The results indicate that investing in process mining tooling before running cutover rehearsals could expose risks of dependency that would otherwise have been overlooked through traditional run-book review for programme managers managing ERP transformation projects. In the case of consumer product businesses, in particular, the possibility of dynamically rescheduling tasks through reinforcement learning may help minimize risk for extending the cutover window into busy trading periods. The AI components are only as good as the data you feed back into them, so organisations with multiple sequential cutovers – such as multi-country ERP rollouts – have the best chance of benefiting from the framework.

Limitations and Future Research

This study is conceptual and evaluative, and the comparative indicators in Section 6 are based on retrospective case data and simulation and do not necessarily reflect the results in a uniform way for all ERP platforms or enterprise sizes. Future studies should include a wider number of consumer product companies in long-term field deployments of the proposed framework, the incorporation of explainable AI techniques to further build trust among practitioners in the scheduling recommendations, and the extension of the proposed framework to supply chain digital twin platforms for additional predictive capabilities beyond the cutover window into post go-live hypercare.

5 CONCLUSION

The aim of this paper was to present an integrated framework that integrates process mining and artificial intelligence in ERP cutover planning within consumer product enterprises. The framework combines discovery-driven conformance checking, predictive analytics, natural language processing and reinforcement-learning-inspired scheduling, which helps combat key shortcomings in the traditional, run-book-based cutover planning process. When compared across three enterprise case profiles that were anonymized, significant gains were seen in cutover duration, delays, manual rework, resource utilization and the number of incidents after go-live. The findings introduce a structured and extensible methodology of cutover planning research and provide a reference architecture that can be used by organizations dealing with complex ERP changes. These results would be further reinforced if they were empirically validated with a larger group of enterprises in the future.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

Disclosure of conflict of interest

The authors declare no conflicts of interest regarding this manuscript.

REFERENCES

[1] van der Aalst, W. M. P. (2016). Process mining: Data science in action (2nd ed.). Springer.

[2] van der Aalst, W. M. P., & Carmona, J. (2018). Process mining: Concepts, techniques, and applications. Business Process Management Journal, 24(1), 2–10.

[3] Adamo, G., Ghidini, C., & Rospocher, M. (2020). Predictive process monitoring: A survey. Information Systems, 91, 101491.

[4] Aguirre, S., Parra, C., & Sepulveda, M. (2017). Methodological proposal for process mining projects. International Journal of Business Process Integration and Management, 8(2), 102–113.

[5] Bezerra, F., & Wainer, J. (2013). Algorithms for anomaly detection of traces in logs of process aware information systems. Information Systems, 38(1), 33–44.

[6] Chapela-Campa, D., Mucientes, M., & Lama, M. (2021). Fast and accurate process discovery based on temporal information. Knowledge-Based Systems, 216, 106790.

[7] Chinosi, M., & Trombetta, A. (2012). BPMN: An introduction to the standard. Computer Standards & Interfaces, 34(1), 124–134.

[8] De Weerdt, J., & Wynn, M. T. (2022). Foundations of process event data. In Process mining handbook (pp. 193–211). Springer.

[9] Ferreira, D. R. (2017). A primer on process mining: Practical skills with data science and business process management. Springer.

[10] Grover, V., Chiang, R. H. L., Liang, T. P., & Zhang, D. (2018). Creating strategic business value from big data analytics: A research framework. Journal of Management Information Systems, 35(2), 388–423.

[11] Hompes, B. F. A., Buijs, J. C. A. M., van der Aalst, W. M. P., Dixit, P. M., & Buurman, J. (2017). Detecting change in processes using comparative trace clustering. Simulation Modelling Practice and Theory, 76, 1–19.

[12] Jans, M., & Hosseinpour, M. (2019). How active learning and process mining can act as continuous auditing catalyst. International Journal of Accounting Information Systems, 32, 44–58.

[13] Kratsch, W., Manderscheid, J., Roglinger, M., & Seyfried, J. (2021). Machine learning in business process monitoring: A comparison of deep learning and classical approaches used for outcome prediction. Business & Information Systems Engineering, 63(3), 261–276.

[14] Leno, V., Polyvyanyy, A., Dumas, M., La Rosa, M., & Maggi, F. M. (2021). Robotic process mining: Vision and challenges. Business & Information Systems Engineering, 63(3), 301–314.

[15] Mahendrawathi, E. R., Astuti, H. M., & Wardhani, I. R. K. (2017). Analysis of customer fulfilment with process mining: A case study in a telecommunication company. Procedia Computer Science, 124, 496–504.

[16] Marquez-Chamorro, A. E., Resinas, M., & Ruiz-Cortes, A. (2018). Predictive monitoring of business processes: A survey. IEEE Transactions on Services Computing, 11(6), 962–977.

[17] Mendling, J., Berente, N., Seidel, S., & Grisold, T. (2020). Pluralism and pragmatism in the information systems field: Implications for process mining. Business Process Management Journal, 26(1), 250–264.

[18] Nguyen, H., Dumas, M., La Rosa, M., & ter Hofstede, A. H. M. (2019). Multi-perspective comparison of business process variants based on event logs. Data & Knowledge Engineering, 121, 1–22.

[19] Rehse, J.-R., Mehdiyev, N., & Fettke, P. (2019). Towards explainable process predictions for industry 4.0 in the DFKI-Smart-Lego-Factory. KI - Kunstliche Intelligenz, 33(2), 181–187.

[20] Reinkemeyer, L. (2020). Process mining in action: Principles, use cases and outlook. Springer.

[21] Rojas, E., Munoz-Gama, J., Sepulveda, M., & Capurro, D. (2016). Process mining in healthcare: A literature review. Journal of Biomedical Informatics, 61, 224–236.

[22] Sarkar, S., & Vercellis, S. (2023). AI-augmented process mining for enterprise resource planning transformation programmes. Decision Support Systems, 167, 113916.

[23] Teinemaa, I., Dumas, M., Rosa, M. L., & Maggi, F. M. (2019). Outcome-oriented predictive process monitoring: Review and benchmark. ACM Transactions on Knowledge Discovery from Data, 13(2), 1–57.

[24] Verbeek, H. M. W., & van der Aalst, W. M. P. (2022). Decomposed replay using hiding and reduction as abstraction. Software and Systems Modeling, 21(1), 267–293.

[25] Wu, Y., Sun, X., & Zhao, L. (2023). Reinforcement learning-based scheduling for ERP cutover planning in manufacturing enterprises. IEEE Access, 11, 34521–34535.