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Process Mining in Banking Logistics: From Identification to Improvement

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Abstract

This paper investigates the application of Process Mining (PM) techniques to redesign and optimize logistics processes within an Iranian bank. The primary aim is to identify inefficiencies, bottlenecks, and process deviations using real-world event log data and to provide data-driven recommendations for process improvement. Data comprising 35,642 event reports related to 16,490 logistics process workflows were extracted from the bank's automation and correspondence systems over six months in 2022. Disco 2.14 was used for data analysis. Results revealed that only 3.6% of product demands conformed to the predefined process model, indicating high process variability and improvement potential. Analyses also showed the average process duration was 5.7 days, exceeding the bank's internal benchmark (three to five days), and the process fulfillment ratio was 83.3%, falling short of the desired target of 95%. Key inefficiencies identified included excessive waiting times for unfulfilled demands (averaging 315.7 days) and bottlenecks in the "Registering the purchase invoice" and "Registering the warehouse receipt" activities. Drawing on these findings, suggestions were proposed to optimize the procurement process, automate manual efforts, and improve alignment with the defined process model. This study contributes to the existing knowledge by providing an empirical case study of PM application in a specific context within the banking industry. The findings underscore the importance of monitoring and managing process conformance, as well as addressing excessive waiting times to improve customer satisfaction and operational efficiency. Limitations of this study include reliance on data from a single bank and a focus on logistics processes. Future research could focus on investigating root causes of process deviations, using PM for predictive analysis, and evaluating the impact of process improvements on key performance indicators.

Keywords: Process mining, Business process redesign, Logistics process, Banking

Introduction

The efficiency and effectiveness of logistics processes within banks are critical determinants of service quality, operational costs, and overall financial performance. These processes, which encompass the procurement, storage, and distribution of essential resources ranging from currency and secure documents to IT equipment and office supplies, often grapple with inherent complexities leading to inefficiencies, inflated costs, and protracted timelines (Lambert et al., 1998). These challenges not only erode profitability but also compromise banks' responsiveness to dynamic market demands and regulatory changes. Efficient Logistics Management in banks can lead to higher financial agility and responsiveness.

Process mining (PM) has emerged as a transformative methodology for analyzing, redesigning, and optimizing business processes by leveraging event log data to uncover actual process flows, identify bottlenecks, and detect deviations from intended workflows (van der Aalst, 2016; 2022). PM is a data-driven methodology based on event log information. Event log data is collected by system implementation in banks and their logistics departments. While PM has been successfully applied in various industries to enhance operational efficiency, compliance, and customer satisfaction (e.g., healthcare, manufacturing), its adoption within the banking sector, particularly for logistics processes, remains surprisingly limited. This gap is particularly concerning given the increasing pressure on banks to streamline operations, reduce costs, and improve service delivery in an intensely competitive landscape. This study aims to address these issues and provide useful techniques that would allow business owners to tackle these challenges. Furthermore, the successful application of PM has been demonstrated even in complex systems, like cross-docking, highlighting its potential applicability to banking logistics (Shams-Shemirani et al., 2024).

Existing research indicates that banks often rely on traditional methods such as manual process analysis and workflow simulations, which are time-consuming, prone to subjective bias, and lack the granularity to identify subtle inefficiencies hidden within complex logistics workflows (Dumas et al., 2018). Moreover, many banking systems are not inherently process-aware, requiring techniques to generate event logs to enable process mining (Pérez-Castillo et al., 2011). The unique characteristics of banking logistics, including stringent security requirements, regulatory compliance demands, and the need for precise tracking of high-value assets, pose specific challenges that may not be adequately addressed by generic PM approaches. In this regard, Park and Kang (2016) highlight the need for adapting PM techniques to specific business contexts to achieve meaningful improvements.

Addressing this gap, this study aims to investigate the feasibility and potential benefits of applying PM techniques to redesign and optimize logistics processes within a leading Iranian bank. By analyzing real-world event log data, the research seeks to uncover hidden inefficiencies, identify root causes of delays and errors, and propose data-driven recommendations for process improvement. The ultimate goal is to demonstrate how PM can enable banks to achieve significant gains in efficiency, cost reduction, and service quality within their logistics operations. The research contributes to the existing knowledge by providing an empirical case study of PM application in a specific context in the banking industry. We demonstrate the impact of PM in an organization in Iran.

This study focuses on improving the logistics process in one of the private banks in Iran using re-engineering methodology and process mining techniques, and aims to answer the following questions:

1- What is the overall efficiency of the banking logistics process?

2- What are the main inefficiencies in this process?

3- What are the possible solutions to improve the efficiency?

Figure 1 illustrates the fundamental data flow in process mining, showcasing the relationship between process definitions, instances, activities, and the event logs used for analysis. This framework, particularly the transformation of event data into process models and performance metrics, directly informed our investigation into redesigning logistics processes (Research Question 1) and identifying key process indicators (Research Question 2) within the bank's logistics operations. This study uses key performance indicators to drive the redesign and optimization of the logistics process in a specific bank.

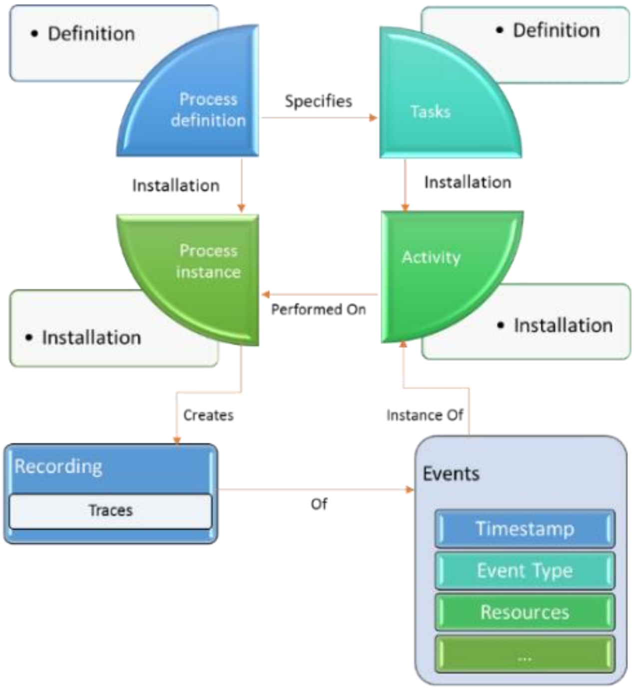

Figure 1. Event report structure, Source: Analysis of Volvo's IT problem management closed processes using ProM and Disco process mining software (Çelik et al., 2016)

Literature Review

The banking sector operates within an increasingly competitive and regulated environment, demanding operational excellence to maintain profitability and customer satisfaction. Efficient logistics processes are vital for the smooth functioning of banks, encompassing the secure management of cash, documents, and other valuable assets. This literature review explores Business Process Reengineering (BPR), Business Process Management (BPM), and Process Mining (PM), evaluating their relevance to optimizing banking logistics and identifying opportunities for further research.

Business Process Reengineering (BPR): A Retrospective and Contemporary View

Business Process Reengineering (BPR), popularized in the early 1990s, advocated a radical overhaul of existing business processes to achieve dramatic performance improvements (Hammer, 1990). BPR aimed to move organizations away from functional silos towards process-oriented structures, emphasizing efficiency and cost reduction (Nakhainejad, 2007). While BPR principles remain relevant, the approach has evolved to incorporate more holistic and adaptive strategies (Battilani et al., 2022). However, the BPR approach often faced criticism for its top-down nature and disregard for the human element, leading to resistance and implementation failures (Caron et al., 1994). As Akhramovich et al. (2024) point out, the successful implementation of any reengineering practice requires careful consideration of organizational culture and workforce participation.

More recently, scholars have revisited BPR, emphasizing the need for a balanced approach that integrates organizational culture and change management (Brandl et al., 2020). A successful BPR initiative must consider not only the technical aspects of process redesign but also the social and behavioral dimensions of organizational change (Elzinga et al., 1995). While BPR offers a valuable framework for radical transformation, it often lacks the analytical tools to identify specific improvement opportunities and to monitor the impact of changes systematically.

Business Process Management (BPM): A Framework for Continuous Improvement

Business Process Management (BPM) provides a structured approach to managing and optimizing business processes continuously. Unlike the one-time, disruptive nature of BPR, BPM focuses on ongoing monitoring, analysis, and improvement of processes to align them with organizational goals (Reijers, 2021). BPM encompasses a wide range of activities, including process modeling, simulation, execution, and performance measurement (van der Aalst, 2021).

The benefits of BPM include increased efficiency, reduced costs, improved customer satisfaction, and enhanced regulatory compliance (Steiner, 2019). BPM initiatives often involve the use of technology to automate and streamline processes, enabling organizations to respond more quickly to changing market conditions (Davenport & Short, 1990). However, BPM can be challenging to implement effectively, requiring strong leadership, a clear understanding of business processes, and a commitment to continuous improvement (Rosemann & vom Brocke, 2014). Gažová et al. (2022) emphasize the impact of Business Process Management on the automation and the technologies of Industry 4.0, which is connected to the technologies and the processes of Logistics.

Recent research has focused on integrating BPM with other management approaches, such as Lean and Six Sigma, to achieve synergistic benefits (Vom Brocke & Rosemann, 2010). Moreover, the rise of digital technologies has led to the emergence of "Intelligent BPM Systems" (iBPMS), which leverage data analytics, machine learning, and artificial intelligence to automate and optimize business processes more effectively (van der Aalst, 2021).

Process Mining (PM): Data-Driven Insights for Process Optimization

Process Mining (PM) offers a data-driven approach to process analysis and improvement by extracting knowledge from event logs (van der Aalst, 2011). PM techniques enable organizations to discover actual process flows, identify bottlenecks, detect deviations from intended workflows, and measure process performance objectively (van der Aalst, 2016). PM is useful to extract data for any kind of business, even if it is based on an existing system, such as the process of a Small-to-Medium Business (Wijnhoven et al., 2023).

Unlike traditional process analysis methods, which rely on subjective opinions and manual data collection, PM leverages data science techniques to provide insights based on real-world process behavior (Sarker, 2021). PM can be applied to a wide range of processes, including those in the banking sector, to improve efficiency, reduce costs, and enhance compliance (Günther & van der Aalst, 2007). Munoz-Gama et al. (2022) and De Roock and Martin (2022) focus on the applications of Process Mining to the healthcare environment, as a leading business process.

However, the application of PM in the banking sector presents unique challenges, including data privacy concerns, regulatory requirements, and the complexity of banking processes (Li et al., 2025). Moreover, many banking systems lack the necessary event log data to support PM analysis, requiring additional effort to extract and transform data from multiple sources (Pérez-Castillo et al., 2011). Turner et al. (2012) emphasize that the real value of PM lies in its practical application and the actionable insights it generates.

Process Mining for Banking Logistics: Opportunities and Challenges

Process Mining has found increasingly important applications in banking environments. Although it has been known to solve fraud detection and loan processing applications, its application to banking logistics remains relatively unexplored. Banking logistics processes, which involve the secure transport and storage of cash, documents, and other valuable assets, are critical for the smooth functioning of banking operations. However, these processes often face challenges such as inefficiencies, security risks, and regulatory compliance issues. Process Mining is considered useful to assist in fraud detection, banking applications, and loan processing, but the literature provides scant application to the logistics aspect, leaving a gap in research for logistics applications.

Applying PM to banking logistics could provide valuable insights into these processes, enabling banks to identify bottlenecks, reduce costs, improve security, and enhance compliance. However, several challenges must be addressed to realize the full potential of PM in this area. These challenges include:

- ✓ Data Availability and Quality: Banking logistics processes often involve multiple systems and stakeholders, making it difficult to obtain complete and accurate event log data.
- ✓ Security and Privacy: Banking logistics data is highly sensitive and must be protected from unauthorized access and disclosure.
- ✓ Regulatory Compliance: Banking logistics processes are subject to strict regulatory requirements, which must be considered when applying PM techniques.
- ✓ Process Complexity: Banking logistics processes can be highly complex, involving multiple steps, decision points, and stakeholders, making it difficult to analyze and improve them using PM.

Conclusion and Research Gaps

This literature review has highlighted the potential of BPR, BPM, and PM to improve banking operations, with a particular focus on logistics. While BPR provides a framework for radical process redesign and BPM offers a structured approach to continuous improvement, PM provides the data-driven insights needed to identify specific improvement opportunities and to monitor the impact of changes objectively. Choueiri and Santos (2021) highlight that process mining assists in dependency discovery in the industry, as well as the application of this technology to manufacturing environments. This technology can be applied to banking environments.

Despite the potential benefits of PM for banking logistics, its application in this area remains relatively unexplored. Future research should focus on addressing the challenges of applying PM to banking logistics, including data availability and quality, security and privacy, regulatory compliance, and process complexity. Moreover, there is a need for more empirical studies that demonstrate the value of PM in improving banking logistics processes in real-world settings. De Weerdt et al. (2012) emphasize that assessing technological processes requires a strong focus on quality, suggesting that future research in banking should account for data quality to support more informed decision-making.

By addressing these research gaps, we can unlock the full potential of PM to transform banking logistics and improve the overall performance of the banking sector.

Research background

Business process reengineering (BPR) and process mining (PM) are increasingly recognized as complementary methodologies for organizational improvement and digital transformation (van der Aalst, 2016; Dumas et al., 2018). BPR provides a structured approach to redesigning business processes for efficiency and effectiveness, while PM offers data-driven insights into existing processes, enabling informed decision-making by leveraging event data (Kirchmer, 2017).

The process begins with a formal “Process Definition”, which specifies the structure and sequence of “Tasks”. When a Task is executed, it creates a “Process Instance”, representing a single execution of the process. Each Process Instance comprises a series of “Activities”, representing individual steps performed. Each Activity generates an “Event”, which is recorded with attributes such as Timestamp, Event Type, and Resources. The collection of Events associated with a process instance forms a “Trace”, which serves as the primary input for process mining algorithms (van der Aalst, 2016). (Fig 3) Understanding the relationship between these core concepts is foundational to understanding the approach used in this study. The ability to correlate the events and the timestamps can be used to improve logistics (Lorenz et al., 2021)

While PM has found applications in diverse domains, including supply chain optimization (Jokonowo et al., 2018), healthcare process improvement (Pereira et al., 2020; de Boer et al., 2025), and fraud detection (Huda et al., 2025), its adoption within the banking sector, particularly in the context of logistics process redesign, remains limited. For example, Jokonowo et al. (2018) demonstrated the effectiveness of PM in optimizing supply chain processes for a manufacturing company, highlighting the potential for reducing cycle times and improving resource utilization. Similarly, de Boer et al. (2025) applied PM to improve patient flow in a hospital, focusing on reducing waiting times and improving resource allocation. However, to date, there is a lack of research exploring the application of process mining for the logistics processes within banking, specifically addressing challenges such as long processing times, high waiting times, and process deviations. This study aims to address this gap by applying process mining techniques to analyze the logistics processes of the Bank, identify key inefficiencies, and develop data-driven recommendations for process improvement.

The study provides a real example of how these steps are implemented by the Logistics department in a bank, by re-engineering them, based on prior steps.

Research Process

The research process followed a structured approach, as depicted in Figure 2, comprising the following key phases:

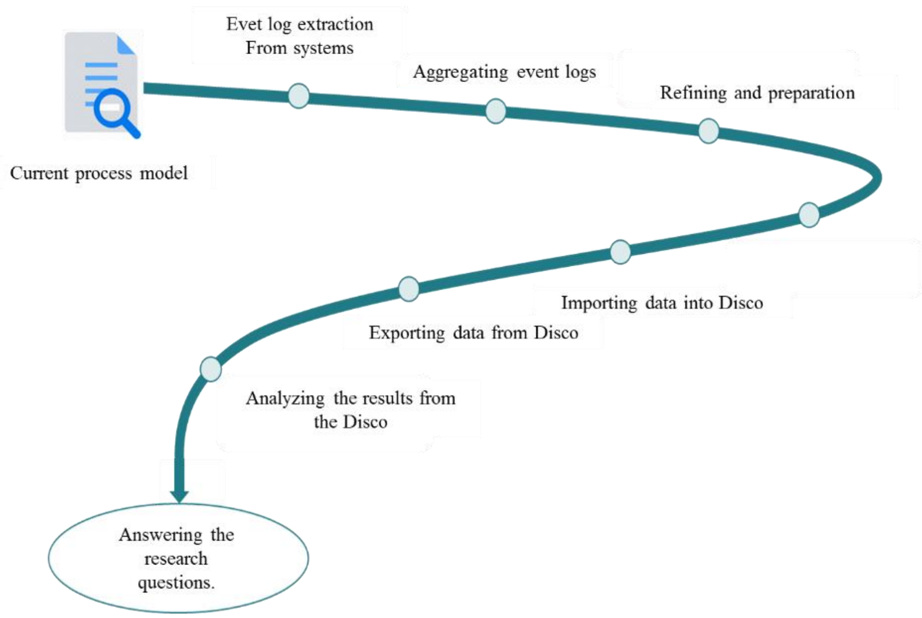

Figure 2. Structured Approach Research Steps

Figure 3 illustrates the fundamental concepts used in process mining, showing how real events form traces based on defined process definitions. The data flows through the processes, as the system implementation works within the banks: The core of process mining begins with a formal "Process Definition", representing a structured framework that outlines the sequence of "Tasks." The process begins when a Task is executed, and creates a "Process Instance". The Event recorded in each Process Instance, which is called "Activity", includes attributes like Timestamp, Event Type, and Resources. These events are saved as "Traces", which serve as the input to the process mining process.

This structured process directly informed the process of Logistics in Banking (Research Question 1), and the Key Performance Indicators (Research Question 2).

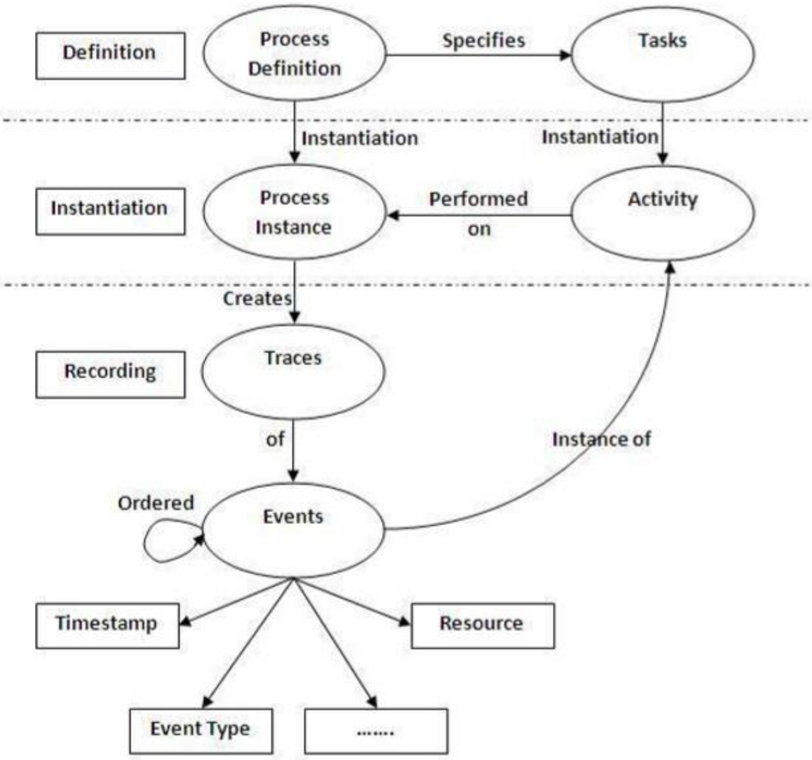

Figure 3. Structure of the event report

Information extracted from the event logs (Table 1) underwent a refinement process to prepare it for subsequent analysis.

Table 1. Required information for the event log

Descriptions	Title	row
Event Counter	Case ID	1
System-Registered Item Request Number	RequestNumber	2
Activity Performed	Activity	3
Activity Start Time	Start Timestamp	4
Requesting Organizational Unit	Departman	5
Item Type	Process section	6
Item Subtype	Sub-process section	7
Item Name	Product Name	8
Delivery Status	Delivery status	9
Request Status	Request status	10

Data Collection and Preparation

A dataset of 35,642 event logs related to 16,490 logistics process workflows was extracted from the bank's automation and correspondence system over six months in 2022. The data was obtained from two modules, the “Correspondence Tracking Module" and the "Warehouse Management System.” To ensure data quality, the following steps were taken.

The data was extracted from the "Administrative Correspondence" and "Warehouse Management System". Every logistics-related process is listed here. The raw data was cleaned and transformed using Excel Power Query to ensure data quality and consistency. This included standardizing date formats, handling missing values, resolving inconsistencies in activity labels, and ensuring consistency in resource names.

- Standardizing Date Formats: Ensuring a consistent date format (YYYY-MM-DD) across all event logs to enable accurate time-based analysis.
- Handling Missing Values: Addressing missing values in key attributes (e.g., resource names, timestamps) through imputation techniques (e.g., replacing missing resource names with "Unknown") or, in cases where imputation was not feasible, removing the affected event logs.
- Resolving Inconsistencies in Activity Labels: Standardizing activity labels to ensure consistent naming conventions (e.g., converting "Register Purchase Invoice" to "Registering the Purchase Invoice").
- Ensuring Consistency in Resource Names: Standardizing resource names to accurately identify the individuals or departments responsible for each activity
- Removing outliers: calculations to detect and treat any outliers that may result in skewing process analysis and KPI values

Process Mining Tools

For process discovery and analysis, Disco 2.14 was chosen. Disco provides advanced capabilities for process visualization, bottleneck analysis, and conformance checking (Günther & van der Aalst, 2007). It allows for a user-friendly experience, which helps analyze the event graphs. This tool was selected, with its automated features allowed to assist with the process analysis and quick understanding. Furthermore, generating process maps proved advantageous, as it required minimal time and provided immediate visibility into the system, enabling faster solution planning.

While other tools like ProM (van der Aalst, 2011) and Celonis (van der Aalst, 2023) exist, Disco was selected for its strengths in visual analytics and suitability for the research objectives.

Table 2 provides a comparison of process Mining tools, highlighting their key features and focus areas.

Table 2. Comparison of Process Mining Tools

Tool	Type	Description	Key Features	Focus Areas	Recent References
Celonis	Commercial	A leading process mining platform for process excellence and execution management.	Process discovery, conformance checking, root cause analysis, process automation, simulation, and real-time monitoring.	End-to-end process optimization, automation, and execution management.	van der Aalst, 2011
Disco	Commercial	User-friendly process mining tool with a focus on visual analytics and ease of use.	Automated process discovery, variant analysis, performance analysis, conformance checking, and root cause analysis.	Process discovery, bottleneck analysis, conformance checking, and quick insights.	Abrehdari, S. H. 2025
Minit	Commercial	Process mining platform that combines process mining with task mining and AI-driven insights.	Process discovery, conformance checking, root cause analysis, task mining integration, and AI-powered recommendations.	Process intelligence, task automation, and operational excellence.	Leno et al., 2021 Ge et al., 2023
ProM	Open Source	A comprehensive open-source process mining framework with a wide range of algorithms and plug-ins.	Process discovery, conformance checking, model repair, social network analysis, organizational mining, and simulation.	Research, algorithm development, complex process analysis, customization.	van der Aalst, 2011

The selection of a process mining tool is a critical decision that can significantly impact the effectiveness of a process mining project. After careful consideration of available options, including both open-source (e.g., ProM) and commercial tools (e.g., Celonis, Disco), this study employed Disco 2.14. Disco was favored for its balance of powerful analytical capabilities and ease of use. Prior research has highlighted Disco's effectiveness in process discovery, bottleneck analysis, and conformance checking (Günther & van der Aalst, 2007). Disco's ability to automatically generate process models from event logs, its intuitive filtering and variant analysis features, and its visual analytics capabilities were particularly well-suited for the challenges of analyzing the bank's complex logistics processes. Furthermore, the ability to quickly generate process maps was advantageous. Compared to more complex environments, DISCO allowed us to immediately view the system and begin planning a solution. The availability of comprehensive documentation and support resources also contributed to the decision to use Disco 2.14.

Methodology

This study adopted a descriptive and applied research design. The research was descriptive because it sought to describe the existing logistics processes in detail. It was also applied because it aimed to improve these processes in practice. The data was analyzed, not only in Disco, but in Excel to detect and remove outliers.

Validation

To ensure the reliability and validity of the research findings, multiple validation steps were taken. First, the discovered process models and identified bottlenecks were presented to process owners and domain experts at the Bank for verification. The experts assessed the accuracy and relevance of the findings. Second, suggested process improvements were also presented to the process owners and domain experts. Furthermore, the results were validated by cross-referencing the reports with the existing banking domain-specific literature.

The findings of the studies were also validated by cross-referencing with already known literature in the banking-specific domain.

Results

This study employed process mining techniques to discover, analyze, and improve the bank's logistics process workflows. The primary objectives were to identify bottlenecks, understand process deviations, and provide data-driven recommendations for process redesign.

Overall Process Flow and Duration

After entering the data and running the Disco software, Figure 4 illustrates the overall diagram of the logistics process. This diagram provides a high-level view of all activities and their connections, with the thickness of the arrows indicating the frequency of transitions between activities.

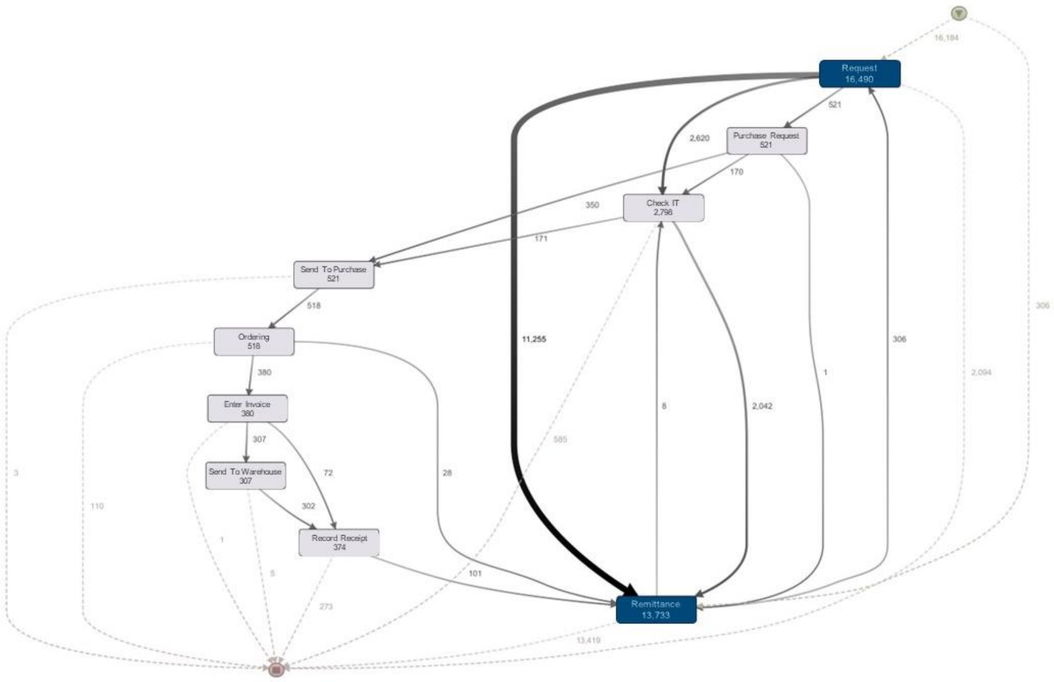

Figure 4. Process map of the bank's logistics process, showing the overall flow of activities and their connections

Analyzing process duration is one of the most effective aspects of process mining. Figure 5 displays the average duration of the logistics process, with the average duration of each activity highlighted.

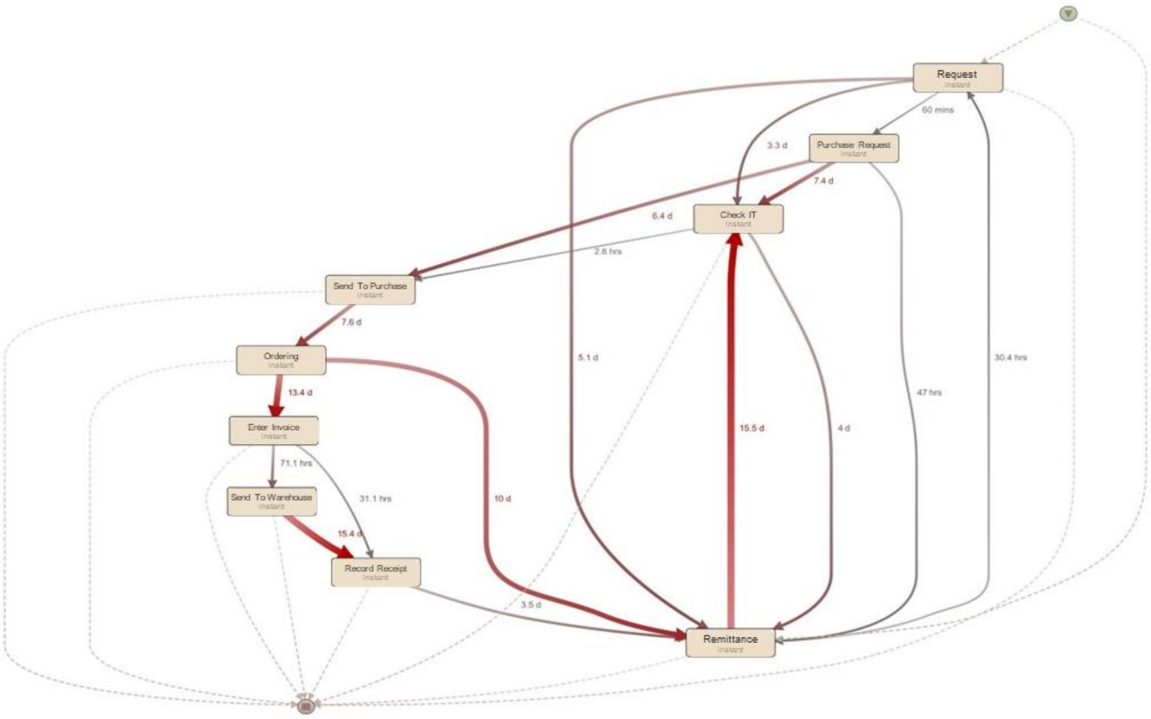

Figure 5. Average duration of each activity in the logistics process

Figure 5 illustrates an overview of the process. The maximum time interval between two activities spans 15.5 days, associated with issuing warehouse remittance and delivering to the applicant, alongside checking through electronic banking. This demand is excluded from the data range as it is identified as a defective product request in the adaptation check. Thus, the maximum time interval between two activities is limited to 15.4 days, relating to sending items to the warehouse and registering the warehouse receipt. According to the software output, the average total process implementation time for completed demands is 5.7 days. Table 3 presents the process flow from one activity to another in the bank's logistics domain, including total time spent.

Table 3. The flow of demands from one activity to another, along with the total time spent in each transition.

Row	From	To	Amount	Total spent time	Ave. spent time
1	Submitting the product demand	Checking and determining the amount by electronic banking	2620	23.4 year	3.2 d
2	Submitting the product demand	Registering a purchase demand	521	21.7 day	0.04 d
3	Submitting the product demand	Issuing the warehouse remittance and delivering it to the customer	11255	157.5 year	5.04 d
4	Submitting the product demand	Checking and determining the amount by electronic banking	170	41.5 month	7.32 d
5	Submitting the product demand	Sending to the purchase process	350	73.3 month	6.28 d
6	Checking and determining the amount by electronic banking	Issuing the warehouse remittance and delivering it to the customer	2042	22.5 year	3.97 d
7	Checking and determining the amount by electronic banking	Sending to the purchase process	171	20.1 day	0.12 d
8	Sending to the purchase process	Registering the order	518	10.8 year	7.5 d
9	Registering the order	Registering the purchase invoice	380	13.9 year	13.17 d
10	Registering the purchase invoice	Sending products to the warehouse	307	29.9 month	2.92 d
11	Sending products to the warehouse	Registering the warehouse receipt	302	12.7 year	15.14 d
12	Sending products to the warehouse	Issuing the warehouse remittance and delivering it to the customer	101	50.3 week	3.49 d

Transition analysis of the logistics process, detailing the flow of demands from one activity to another. The "Amount" column indicates the number of demands that followed a specific path, while the "Total Spent Time" column represents the cumulative time spent on all demands transitioning between those two activities. This table provides insights into the most frequent process paths and the time consumption associated with each transition, revealing potential areas for process optimization.

Analysis of Undelivered Items

To understand the reasons for unfulfilled demands, the "Issuing the warehouse remittance and delivering to the customer" activity was temporarily removed from the process model. Figure 6 illustrates the resulting process flow, highlighting the points where demands are currently "stuck."

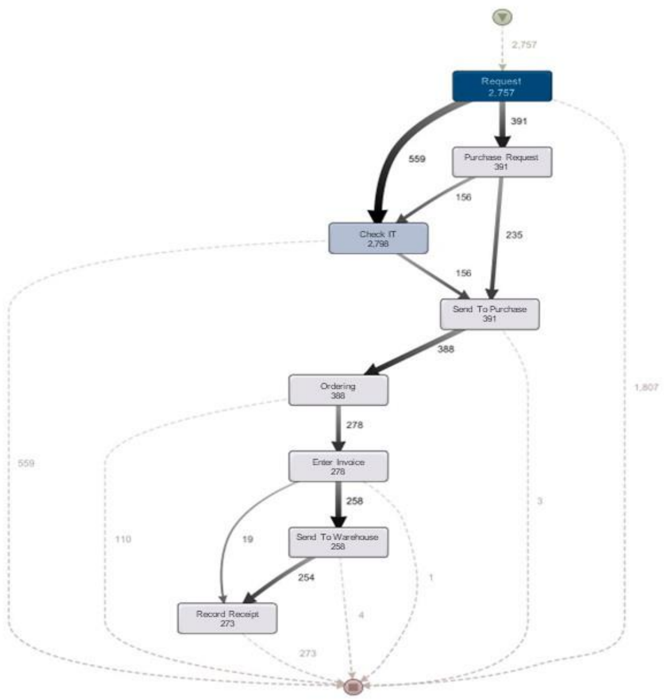

Figure 6. Process map showing the current status of unfinished demands, with the final delivery activity removed

Unfinished requests refer to those that have not reached the stage of warehouse remittance and delivery to the applicant. As depicted, 2,757 product demands did not complete the process, resulting in the desired product not being delivered. To effectively analyze these demands, it is essential to evaluate the unfinished demands for each activity, as presented in Table 4. This analysis reveals the specific causes of these bottlenecks in the process and can provide insights for improvement.

Table 4. Number of demands that are currently unfinished at each stage of the logistics process

<table>
<tr><th>Row</th><th colspan="2">From activity</th><th>Number of unfinished</th></tr>
<tr><td>1</td><td colspan="2">Submitting the product demand</td><td>1807</td></tr>
<tr><td>2</td><td colspan="2">Checking and determining the amount by electronic banking</td><td>559</td></tr>
<tr><td>3</td><td colspan="2">Registering a purchase demand</td><td>3</td></tr>
<tr><td rowspan="3">4</td><td rowspan="3">The process of purchasing goods and services</td><td>Order registration</td><td>110</td></tr>
<tr><td>Registering the purchase invoice</td><td>1</td></tr>
<tr><td>Sending products to the warehouse</td><td>4</td></tr>
<tr><td>5</td><td colspan="2">Registering the warehouse receipt</td><td>273</td></tr>
<tr><td colspan="3">Total</td><td>2757</td></tr>
</table>

In the logistics process of banks, there are two stages for reviewing requests, which are conducted by support deputies and electronic banking deputies, depending on the product type. Based on the results, 391 demands remain incomplete after passing through stages of demand review, resulting in undelivered products for customers. Additionally, 273 demands were halted at the stage of registering the warehouse receipt, which is the step before issuing the warehouse remittance and delivering to the customer.

Table 5. The ten demands that have been pending for the longest duration, categorized by last stage, category, and sub-category

Row	Last stage	Number	Date of the last stage	Category	Sub-category	Delay time
1	Registering the order	1	2022/4/20	Consumption	Essentials	423
2	Registering the order	1	2022/4/21	Consumption	Essentials	422
3	Registering the invoice	2	2022/4/26	Properties	Essentials	417
4	Registering the order	38	2022/5/2	Bank stamp	Bank stamp	411
5	Registering the invoice	2	2022/5/3	Properties	Furniture and fixtures	410
6	Registering the invoice	2	2022/5/5	Consumption	Stationary	408
7	Registering the order	5	2022/5/6	Properties	Furniture	407
8	Registering the invoice	1	2022/5/7	Properties	Electronic appliances	406
9	Registering the order	1	2022/5/10	Consumption	Essentials	403
10	Registering the invoice	2	2022/5/12	Properties	Electronic appliances	401

As shown in Table 5, some undelivered demands have lasted over 400 days since their last activity. The average period from the last activity until the date of receiving the report for the 391 undelivered demands is approximately 315.7 days. The categories and sub-categories of these demands are critical factors for determining process improvement strategies.

Process Discovery and Conformance

Analysis of 35,642 event reports showed that only 3.6% of product demands matched the predefined process model, revealing significant process variability and improvement potential. Process discovery exposed a complex network with 23 diverse workflow types, consistent with research showing higher variability in flexible processes (van Beest et al., 2019; Karbasi et al., 2024).

Performance Analysis and Bottleneck Identification

To identify bottlenecks and analyze them, it is necessary to measure and analyze key performance indicators in this process.

Table 6. Key Performance Indicators of the Logistics Process

Row	Title	Description	Value	Standard Deviation	Interpretation/Benchmark
1	Process duration	Average time between demand initiation and product delivery	5.7 days	2.1 days	Acceptable range = 3-5 days, indicating a need for reduction
2	Fulfillment ratio	Percentage of demands successfully fulfilled	83.3%	12.5%	Benchmark = 95%, suggesting significant room for improvement
3	Purchase ratio	Percentage of demands requiring external purchase	3.2%	1.1%	Relatively low, indicating efficient inventory management in most cases
4	Waiting time	Average time an unfulfilled demand remains pending	315.7 day	95.4 day	Unacceptably high, indicating severe delays in fulfilling outstanding demands

Note: To assess the conformity of process behavior, sample standard deviations of activity cycle times were calculated for each activity, using Disco. Elevated standard deviations can indicate deviations from the intended process model.

The data reveals concerning issues with "process duration" and "waiting time". With an average process duration of 5.7 days (SD = 2.1 days), the process is noticeably longer than the bank's internal benchmark of 3-5 days. Furthermore, the average waiting time for unfulfilled demands is extremely high at 315.7 days (SD = 95.4 days). This suggests problems with both process efficiency and responsiveness. The relatively low purchase ratio (3.2%) indicates efficient inventory management for most demands, which can be used to help the fulfillment and waiting ratio. The longest activity times within the process were related to registering the purchase invoice and registering the warehouse receipt, confirming these as primary bottlenecks.

Answering Research Questions

The results of the process mining analysis provide data-driven answers to the research questions posed in the introduction. The following sections address each question, drawing on the KPIs and process insights generated from the analysis.

What is the overall efficiency of the banking logistics process?

The overall efficiency of the banking logistics process at the Bank is suboptimal. As shown in Table 3, the average process duration is 5.7 days, exceeding the bank's internal benchmark of 3-5 days. Furthermore, the process fulfillment ratio is only 83.3%, falling short of the desired target of 95%. These metrics indicate a clear need for improvement in process efficiency.

What are the main inefficiencies in this process?

The primary inefficiencies in the logistics process are related to excessive waiting times and process deviations. The average waiting time for unfulfilled demands is a concerning 315.7 days (Table 5), indicating bottlenecks in the procurement or inventory management stages.

Additionally, the low process conformance rate of 3.6% suggests a lack of adherence to the defined process model, contributing to delays and inconsistencies. The time spent registering the purchase invoice and registering the warehouse receipt has been proven to cause a long delay in the process.

What are the possible solutions to improve the efficiency?

Based on the process mining analysis, several potential solutions can be implemented to improve the efficiency of the logistics process. Streamlining the procurement process, potentially through automation or improved supplier communication, could reduce waiting times and improve the fulfillment ratio. Implementing process controls and training programs to increase conformance to the defined process model can also minimize deviations and reduce delays. Further work is being done to create models for the KPI to improve it.

The study suggested several improvement actions. To assess the impact of improvements:

- future research should apply the process mining framework implemented in this study;
- performance indicators before and after the process changes should be compared to measure their effect;
- Data from financial databases should be analyzed to determine the impact on the bank’s economic performance.

Discussion

This study investigated the logistics processes within a bank using process mining techniques. The analysis of 35,642 event logs revealed several key insights into the efficiency, conformance, and bottlenecks within these processes. This section will discuss the implications of these findings in relation to the existing literature, highlight the contributions of this study, and suggest directions for future research.

Comparison with Existing Literature

One of the key findings of this study was the significant deviation from the defined process model, with only 3.6% of product demands adhering to the predetermined process. This finding is consistent with previous research that has highlighted the challenges of process conformance in complex and dynamic environments. However, the specific conformance rate observed in this study is lower than those reported in other studies, potentially reflecting the unique characteristics of the bank's logistics processes, such as the wide range of products handled and the involvement of multiple departments.

The analysis also identified excessive waiting times as a major inefficiency in the logistics process, with an average waiting time for unfulfilled demands of 315.7 days (Table

5). This finding is particularly concerning, as prolonged waiting times can lead to customer dissatisfaction, increased costs, and reduced operational efficiency. While previous studies have also identified waiting times as a significant issue in service processes (Caruelle et al., 2023), the magnitude of the waiting times observed in this study suggests a more systemic problem that requires urgent attention.

Furthermore, the study identified "Registering the purchase invoice" and "Registering the warehouse receipt" as key bottlenecks in the logistics process. These activities often involve manual data entry, verification, and approval steps, which can be time-consuming and error-prone. Automating these activities could significantly improve the efficiency of the logistics process.

Contributions and Implications

This study makes several important contributions to the field of process mining and banking operations. First, it provides a detailed analysis of the logistics processes within a bank, a context that has received relatively little attention in the existing literature. By applying process mining techniques to this specific context, the study sheds light on the unique challenges and opportunities associated with managing logistics operations in a banking environment.

Second, the study demonstrates the practical value of process mining for identifying inefficiencies, understanding process deviations, and developing data-driven recommendations for process improvement. By analyzing real-world event logs, the study provides actionable insights that can be used to improve the efficiency and effectiveness of the bank's logistics processes.

Third, the study highlights the importance of considering both process conformance and performance when evaluating the efficiency of business processes. While previous studies have often focused on either process conformance or performance, this study demonstrates the value of integrating both perspectives to gain a more holistic understanding of process behavior.

The findings of this study have several important implications for banking managers and practitioners. First, they underscore the need to monitor and manage process conformance to ensure that processes are executed as intended. This can be achieved through the implementation of process controls, training programs, and real-time monitoring systems.

Second, the findings highlight the importance of addressing excessive waiting times to improve customer satisfaction and operational efficiency. This can be achieved through streamlining the procurement process, automating manual activities, and improving communication between departments.

Third, the findings suggest that process mining can be a valuable tool for identifying and addressing inefficiencies in banking operations. By analyzing real-world event logs, process mining can provide actionable insights that can be used to improve process performance and reduce costs.

Limitations

This study has several limitations that should be acknowledged. First, the study is based on data from a single bank, which may limit the generalizability of the findings to other banking institutions. Future research should replicate this study in other banks to validate the findings and to identify any contextual factors that may influence process behavior.

Second, the study focuses on the logistics processes within the bank. While these processes are important, they represent only a subset of the bank's overall operations. Future research should expand the scope of the analysis to include other key processes, such as customer onboarding, loan processing, and fraud detection.

Third, the study relies on event log data extracted from the bank's information systems. The accuracy and completeness of this data may be affected by data quality issues, such as missing values, incorrect timestamps, and inconsistent activity labels. Future research should focus on improving data quality to enhance the reliability of process mining results.

Future Research Directions

This study opens up several avenues for future research. First, future studies could investigate the root causes of process deviations and waiting times in greater detail. This could involve conducting interviews with process participants, analyzing documents, and observing process execution in real-time.

Second, future studies could explore the use of process mining to predict future process behavior. This could involve developing predictive models that forecast process outcomes, such as the likelihood of a demand being fulfilled on time or the risk of a process deviation occurring.

Third, future studies could investigate the impact of process improvements on key performance indicators, such as customer satisfaction, operational efficiency, and financial performance. This could involve conducting controlled experiments or quasi-experimental studies to measure the effects of process changes.

Finally, future studies could explore the ethical and social implications of process mining in the banking sector. This could involve investigating issues such as data privacy, algorithmic bias, and the impact of process automation on the workforce.

Conclusion

This study has provided a comprehensive analysis of the logistics processes within a bank, leveraging process mining techniques to uncover inefficiencies, identify bottlenecks, and assess process conformance. While prior studies have demonstrated the value of process mining in areas such as fraud detection and loan processing (Esmail et al., 2023), this research highlights its potential for optimizing internal operational processes, specifically logistics. The analysis of 35,642 event logs revealed a significant gap between the defined process model and actual process execution, with only 3.6% of product demands adhering to the predetermined flow. This lack of conformance, coupled with excessive waiting times for unfulfilled demands (averaging 315.7 days), indicates a pressing need for process improvement.

The study identified key bottlenecks in the "Registering the purchase invoice" and "Registering the warehouse receipt" activities, highlighting the importance of streamlining these processes to enhance overall efficiency. By quantifying the performance of the logistics process and pinpointing areas for improvement, this research provides valuable insights for banking managers and practitioners seeking to optimize their operations.

While the findings of this study are specific to the logistics processes within a single bank, the methodology and insights can be applied to other banking institutions and service organizations facing similar challenges. The use of process mining as a data-driven approach offers a powerful means of understanding and improving complex business processes, leading to increased efficiency, reduced costs, and improved customer satisfaction.

Future research should focus on investigating the root causes of process deviations and waiting times in greater detail, exploring the use of process mining for predictive analysis, and evaluating the impact of process improvements on key performance indicators. Furthermore, research is needed to address the ethical and social implications of process mining in the banking sector, ensuring that these techniques are used responsibly and ethically.

In conclusion, this study demonstrates the potential of process mining to transform banking operations by providing data-driven insights that can be used to improve process performance and achieve organizational goals. By embracing process mining and other data analytics techniques, banks can unlock new opportunities for innovation, efficiency, and customer value.

Conflict of interest

The authors declare that there is no conflict of interest regarding the publication of this article.

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References

Abrehdari, S. H. (2025). Leveraging the Process Mining Technique to Optimize Data Preparation Time in a Database Used as an Automated Data Delivery Center. *MethodsX*, 103428.

Akhramovich, K., Serral, E., & Cetina, C. (2024). A systematic literature review on the application of process mining to Industry 4.0. *Knowledge and Information Systems*, *66*(5), 2699-2746.

Battilani, C., Galli, G., Arecco, S., Casarino, B., Granero, A., Lavagna, K., ... & Damiani, L. (2022). Business process re-engineering in public administration: The case study of Western Ligurian Sea Port Authority. *Sustainable Futures*, *4*, 100065.

Brandl, F. J., Ridolfi, K. S., & Reinhart, G. (2020). Can we adopt the Toyota kata for the (re-) design of business processes in the complex environment of a manufacturing company?. *Procedia CIRP*, *93*, 838-843. https://doi.org/10.1016/j.procir.2020.03.086

Caron, J. R., Jarvenpaa, S. L., & Stoddard, D. B. (1994). Business Reengineering at CIGNA Corporation: Experiences and Lessons Learned from the First Five Years. *MIS Quarterly*, *18*(3), 233–250. https://doi.org/10.2307/249617

Caruelle, D., Lervik-Olsen, L., & Gustafsson, A. (2023). The clock is ticking—Or is it? Customer satisfaction response to waiting shorter vs. longer than expected during a service encounter. *Journal of Retailing*, *99*(2), 247-264.

Çelik, U., Akçetin, E., & Yaldır, A. (2016). Analysis of Volvo IT's Closed Problem Management Processes By Using Process Mining Software ProM and Disco. *Alphanumeric Journal*, *4*(2), 171-182.

Choueiri, A. C., & Santos, E. A. P. (2021). Discovery of path-attribute dependency in manufacturing environments: A process mining approach. *Journal of Manufacturing Systems*, *61*, 54-65.

Davenport, T. H., & Short, J. E. (1990). *The new industrial engineering: information technology and business process redesign*. Sloan Management Review, 31(4), 11-27.

der Aalst, V., & Mining, W. P. (2011). *Discovery, Conformance and Enhancement of Business Processes*. Media; Springer: Berlin/Heidelberg, Germany, 136. https://doi.org/10.1007/978-3-642-19345-3

de Boer, T. R., Arntzen, R. J., Bekker, R., Buurman, B. M., Willems, H. C., & van der Mei, R. D. (2025). Process mining on national health care data for the discovery of patient journeys of older adults. *Journal of the American Medical Directors Association*, *26*(1), 105333.

De Roock, E., & Martin, N. (2022). Process mining in healthcare–An updated perspective on the state of the art. *Journal of biomedical informatics*, *127*, 103995.

De Weerdt, J., De Backer, M., Vanthienen, J., & Baesens, B. (2012). A multi-dimensional quality assessment of state-of-the-art process discovery algorithms using real-life event logs. *Information systems*, *37*(7), 654-676.

Dumas, M., Rosa, M., Mendling, J., & Reijers, A. H. (2018). *Fundamentals of business process management*. Springer-Verlag.

Elzinga, D. J., Horak, T., Lee, C. Y., & Bruner, C. (1995). Business process management: survey and methodology. *IEEE transactions on engineering management*, *42*(2), 119-128.

Esmail, F. S., Alsheref, F. K., & Aboutabl, A. E. (2023). Review of loan fraud detection process in the banking sector using data mining techniques. *International journal of electrical and computer engineering systems*, *14*(2), 229-239.

Gažová, A., Papulová, Z., & Smolka, D. (2022). Effect of business process management on level of automation and technologies connected to industry 4.0. *Procedia Computer Science*, *200*, 1498-1507.

Ge, J., Sigsgaard, K. W., Mortensen, N. H., Hansen, K. B., & Agergaard, J. K. (2023, June). Structured process mining in maintenance performance analysis: a case study in the offshore oil and gas industry. In *2023 9th International Symposium on System Security, Safety, and Reliability (ISSSR)* (pp. 306-313). IEEE.

Günther, C. W., & Van Der Aalst, W. M. (2007, September). Fuzzy mining–adaptive process simplification based on multi-perspective metrics. In *International conference on business process management* (pp. 328-343). Springer Berlin Heidelberg.

Hammer, M. (1990). Reengineering work. *Harvard business review*, *68*(4), 104-112.

Huda, S., Shidik, G. F., Rafrastara, F. A., & Abdollah, M. (2025). Hybrid Process Mining and Fuzzy Relation Weighting for Process Violation Weighting in Fraud Detection. *International Journal of Intelligent Engineering & Systems*, *18*(5).

Jokonowo, B., Claes, J., Sarno, R., & Rochimah, S. (2018). Process mining in supply chains: a systematic literature review. *International Journal of Electrical and Computer Engineering*, *8*(6), 4626-4636.

Karbasi, A., Mahdikhani, M., Gerschberger, M., & Aghaie, S. (2024). Longitudinal analysis of production process variability: an organizational information processing theory perspective. *Business Process Management Journal*, *30*(6), 1764-1782.

Kirchmer, M. (2017). *High performance through business process management*. West Chester: Springer.

Lambert, D. M., Stock, J. R., & Ellram, L. M. (1998). *Fundamentals of logistics management*. McGraw-Hill/Irwin.

Leno, V., Polyvyanyy, A., Dumas, M., La Rosa, M., & Maggi, F. M. (2021). Robotic process mining: vision and challenges. *Business and Information Systems Engineering*, *63*(3), 301-314.

Lorenz, R., Senoner, J., Sihn, W., & Netland, T. (2021). Using process mining to improve productivity in make-to-stock manufacturing. *International Journal of Production Research*, *59*(16), 4869-4880.

Li, Y., Ni, Z., & Xiao, B. (2025). Domain Knowledge-Enhanced Process Mining for Anomaly Detection in Commercial Bank Business Processes. *Systems*, *13*(7), 545.

Munoz-Gama, J., Martin, N., Fernandez-Llatas, C., Johnson, O. A., Sepúlveda, M., Helm, E., ... & Zerbato, F. (2022). Process mining for healthcare: Characteristics and challenges. *Journal of Biomedical Informatics*, *127*, 103994.

Nakhainejad, M. (2007). Reengineering processes with an emphasis on police. *Police Human Development Monthly*, 9-33.

Park, S., & Kang, Y. S. (2016). A study of process mining-based business process innovation. *Procedia Computer Science*, *91*, 734-743.

Pereira, G. B., Santos, E. A. P., & Maceno, M. M. C. (2020). Process mining project methodology in healthcare: a case study in a tertiary hospital. *Network Modeling Analysis in Health Informatics and Bioinformatics*, *9*(1), 28. https://doi.org/10.1007/s13721-020-00227-w

Pérez-Castillo, R., Weber, B., Pinggera, J., Zugal, S., de Guzmán, I. G. R., & Piattini, M. (2011). Generating event logs from non-process-aware systems enabling business process mining. *Enterprise Information Systems*, *5*(3), 301-335.

Reijers, H. A. (2021). Business Process Management: The evolution of a discipline. *Computers in Industry*, *126*, 103404. https://doi.org/10.1016/j.compind.2021.103404

Rosemann, M., & vom Brocke, J. (2014). The six core elements of business process management. In *Handbook on business process management 1: introduction, methods, and information systems* (pp. 105-122). Springer Berlin Heidelberg.

Sarker, I. H. (2021). Data science and analytics: an overview from data-driven smart computing, decision-making and applications perspective. *SN Computer Science*, *2*(5), 377.

Shams-Shemirani, S., Tavakkoli-Moghaddam, R., Amjadian, A., & Motamedi-Vafa, B. (2024). Simulation and process mining in a cross-docking system: a case study. *International Journal of Production Research*, *62*(13), 4902-4925.

Steiner, F. (2019). Industry 4.0 and business process management. *Tehnički glasnik*, *13*(4), 349-355.

Turner, C. J., Tiwari, A., Olaiya, R., & Xu, Y. (2012). Process mining: from theory to practice. *Business process management journal*, *18*(3), 493-512.

van Beest, N., Groefsema, H., García-Bañuelos, L., & Aiello, M. (2019). Variability in business processes: Automatically obtaining a generic specification. *Information Systems*, *80*, 36-55.

Vom Brocke, J., & Rosemann, M. (2010). *Handbook on business process management* (Vol. 2). Heidelberg: Springer.

Van Der Aalst, W. (2016). Data science in action. In *Process mining: Data science in action* (pp. 3-23). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-662-49851-4.

van der Aalst, W. M. (2021, September). Using free-choice nets for process mining and business process management. In *2021 16th Conference on Computer Science and Intelligence Systems (FedCSIS)* (pp. 9-15). IEEE. http://dx.doi.org/10.15439/2021F002

Van der Aalst, W. M. (2022). Process mining: a 360 degree overview. In *Process mining handbook* (pp. 3-34). Cham: Springer International Publishing.

Wijnhoven, F., Hoffmann, P., Bemthuis, R., & Boksebeld, J. (2023). Using process mining for workarounds analysis in context: Learning from a small and medium-sized company case. *International Journal of Information Management Data Insights*, *3*(1), 100163.

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