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Case Study

From Data to Improvement: Analyzing Performance and Identifying Bottlenecks in the Lending Process with a Data-Driven Process Mining Approach

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ABSTRACT

The loan approval process, characterized by its complexity, path diversity, and time sensitivity, has long been a critical domain for enhancing operational efficiency and customer satisfaction in the banking sector. This study aims to analyze performance and identify bottlenecks within the loan approval process of a financial institution using a process mining approach. The research utilizes data from the BPI Challenge 2012 dataset, which contains over 13,000 loan applications. A quantitative, data-driven methodology was employed, consisting of seven sequential stages: data preparation, process discovery, performance analysis, bottleneck identification, resource analysis, conformance checking, and, finally, the formulation of improvement strategies and continuous monitoring. The results reveal that the loan approval process exhibits a relatively long cycle time, a high rate of rejected or canceled applications, substantial workload concentration among a limited number of users, and low conformance with the reference model. The main bottlenecks were detected in the Application Completion and Credit Assessment stages, while many process deviations were attributed to repetitive or non-standard task sequences. Based on these insights, several improvement strategies were proposed, including the adoption of digital checklists, workload redistribution, standardization of main process paths, automation of time-consuming activities, and deployment of real-time monitoring tools. These actions are expected to improve productivity, reduce operational costs, and enhance customer satisfaction in the banking industry.

KEYWORDS:

Process Mining, Bank Loan Process, Bottleneck Identification, Performance Analysis

JEL Classification: C81, C51, E59, G21

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Banking processes, particularly in the lending domain, are inherently complex, multi-stage, and entail numerous controls and approvals. These complexities present banks and financial institutions with challenges such as extended processing times, high error rates, and substantial operational costs, which can ultimately lead to diminished customer satisfaction, lost financial opportunities, and reduced productivity (Sivasatyanarayanareddy, 2024). Consequently, delays in the loan review and approval process—one of the most critical banking services—can directly impact both customer satisfaction and the organization's financial performance.

Despite the significance of this process, many financial institutions continue to rely on traditional analytical methods for process improvement. Faced with large volumes of data and the increasing complexity of workflows, these traditional methods exhibit limited capabilities in identifying underlying issues and facilitating continuous improvement. The prevailing challenges, particularly in accurately pinpointing bottlenecks and analyzing performance using real-world data, underscore the need to adopt modern, data-driven approaches.

Process mining, an innovative approach based on event data recorded in process-aware information systems, offers a robust toolset for discovering the actual process model, checking conformance, and identifying areas for improvement (Van der Aalst, 2019). By automatically analyzing workflows, this methodology can detect delays, inefficiencies, and resource-allocation issues, thereby providing actionable insights to enhance process performance (John-Otumu et al., 2015; Krajčovič et al., 2024).

Process mining techniques encompass three main areas: process discovery, conformance checking, and process enhancement (dos Santos Garcia et al., 2019). These techniques enable organizations to evaluate process performance using real-world data, make informed decisions, and respond more flexibly to environmental changes (Khan et al., 2023). A primary advantage of process mining is its ability to bridge data mining and process management, facilitating the extraction of hidden realities within event-driven data. Beyond discovering the actual process structure and identifying the most frequent paths, this approach enables researchers to analyze performance metrics such as cycle time, mean and median execution times, and points of delay (Lashkevich et al., 2023). Furthermore, by identifying bottlenecks and costly activities, process mining enables the formulation of targeted improvement proposals. From an organizational perspective, human resource analysis within this framework reveals how workloads are distributed among users and highlights the risks associated with the concentration of activities on a limited number of individuals. Additionally, assessing the degree to which a process conforms to a reference model is another significant benefit; it exposes deviations and non-standard activities, laying the groundwork for improved process efficiency and cohesion. Therefore, as a data-driven approach, process mining provides a comprehensive foundation for the precise, evidence-based evaluation of processes, and it is employed in this study to analyze the lending process (Velasquez et al., 2023).

Recently, methodologies such as Business Process Management (BPM), administrative automation, and continuous process improvement have emerged as key tools for enhancing organizational productivity. Developed with the aim of standardizing activities, accelerating execution speeds, and mitigating errors, these approaches demonstrate high efficacy in structured workflows, such as manufacturing or repetitive services (Chehrehpak et al., 2024). Within the banking sector, these paradigms have been utilized to design lending workflows, develop standardized forms, assign responsibilities, and integrate customer assessment systems. The fundamental advantage of these methods lies in establishing order, control, and process traceability. However, experience has shown that in service processes such as lending, these approaches face serious limitations. The high variability of customer files, differences in documentation and financial conditions, the need for human decision-making, and the reliance on interactions among multiple organizational units often cause the actual process to deviate from the designed model. Furthermore, in many banks, process improvement is based on the experience or assumptions of employees rather than actual data. Consequently, improvement measures are sometimes superficial and imprecise, failing to result in a real reduction in response time or an increase in customer satisfaction.

In response to these challenges, modern data-driven approaches like process mining have emerged as a new generation of process analysis and improvement tools. By relying on actual data recorded in banking systems, process mining provides an accurate picture of the real execution of the lending process. This method enables the discovery of frequent paths, measurement of cycle time, identification of bottlenecks, human resource analysis, and assessment of the process's conformance with a reference model. The key advantage of process mining over traditional approaches is its reliance on actual evidence rather than subjective perceptions; thus, the actual performance of the loan process can be analyzed objectively and in a data-driven manner, enabling the implementation of effective, targeted reforms. As a result, this approach is considered a powerful tool for increasing efficiency, transparency, and data-driven decision-making in the banking industry (Khoroushi & Khoroushi, 2024). In the domain of loan application processes, process mining enables visualization of the process flow, quantification of delays, identification of constraining activities or resources, and analysis of the root causes of inefficiency. Analyzing key performance indicators such as cycle time, waiting time between activities, and resource utilization rates helps better understand the impact of bottlenecks on throughput and service quality, paving the way for improvement solutions.

Accordingly, the objective of this research is to conduct a comprehensive analysis of bottlenecks and the performance of the loan application process in a real-world scenario, using recorded data and process mining tools. Drawing on data from the BPI Challenge 2012, this study seeks to identify constraining activities and resources, quantify and visualize bottlenecks, and provide insights to improve efficiency and reduce operational costs.

The research questions are as follows:

- What is the actual process model derived from the information system data?
- Which activities or parts of the process take the most time and are identified as bottlenecks?
- How can practical recommendations for improving this process be provided using process mining techniques?

The results of this research can be used to redesign financial processes, increase operational productivity, and enhance the banking customer experience.

Literature Review

The growing need of organizations to understand how their processes are actually executed has been the primary motivation for the development and expansion of process mining techniques. This approach, as a subfield of data mining, aims to extract knowledge from massive volumes of data and examine the details of running processes. Process mining is an integration of data mining and business process management (Ceravolo et al., 2023) that combines information science with statistical and analytical technologies to provide a comprehensive and adaptable method for process analysis (Krajčovič et al., 2024).

Process mining focuses on analyzing event data to extract useful knowledge about business processes. In fact, process mining acts as a bridge between traditional model-based process analysis (Nnamdi & Telukdarie, 2020) and data analytics techniques (Ghasemi & Amyot, 2020). Similar to data mining, process analysis techniques utilize data features (or variables) present in event logs to learn useful knowledge for process improvement (Mohammadi et al., 2023). By employing process mining algorithms, models can be extracted from data recorded in information systems, providing valuable insights into an organization's actual processes (Suriadi et al., 2014). Utilizing event logs, process mining enables the analysis and improvement of processes that are often overlooked by people, machines, and software (Van der Aalst, 2013). By extracting relevant information from information systems, this approach provides a data-driven method for improving business processes (Nguyen et al., 2014) and can enhance business operations through the analysis of activities recorded in event logs (Horita et al., 2020).

The core idea of process mining encompasses the discovery, conformance, and enhancement of actual processes using knowledge extracted from recorded events. The first and most common phase is process discovery. In this phase, the actual process model is extracted from event data to determine how process instances are truly executed and to identify frequent paths (Van der Aalst et al., 2004). In the conformance phase, the discovered model is compared with the existing reference model to identify and measure the extent and exact locations of deviations. This step verifies whether the implemented process complies with the designed process (Rozinat & Van der Aalst, 2008). Deviation mining involves extracting business rules from event logs that can explain the root causes of positive or negative deviations (Nguyen et al., 2014). Finally, the enhancement and development phase aims to refine and optimize the existing model using actual execution data. This stage helps analysts identify shortcomings, bottlenecks, and process inefficiencies, and propose corrective actions (Li et al., 2016). Process mining techniques have successfully driven improvements in quality, compliance, and process optimization in leading companies (Helm et al., 2020). From another perspective, these techniques are divided into two categories: structural analysis and behavioral analysis. Structural analysis aims to find a structural representation of the process from event logs (e.g., process models) that facilitates performance analysis and conformance checking and serves as a basis for process redesign. In behavioral analysis, the goal is to find a set of behaviors (e.g., activity patterns) that strongly correlate with a target variable. Behavioral analysis is commonly used for deviation extraction and predictive monitoring, leveraging trained classifiers such as decision trees, random forests, and neural networks.

Furthermore, in some contexts, process models are considered a source of generalized behaviors for descriptive analysis (Nguyen et al., 2017).

In an article, Karimi et al. (2021) investigated the intelligent prediction of the occurrence time of key flight events and implemented a process discovery method from both control-flow (process) and temporal perspectives. Using a process mining approach, this research dynamically predicted the timing and analyzed the temporal behavior of key future flight events based on the past behavior of each flight. Applying the results of this research reduces waiting times, prevents passenger congestion, and increases satisfaction through timely flight announcements. It also proposed an intelligent scheduling program for the air transport system and improved the scheduling of airport facilities.

Hosseini and Aghdasi (2023), in an article using the process mining approach, conducted a social network analysis and identified key actors in process execution. The results of this research facilitated supplier selection in complex projects, which is one of the most impactful decisions on a company's quality, cost, and performance.

An article titled "Discovery and Analysis of the Purchasing Process in a Project-Oriented Organization Using Process Mining" introduced a framework that, by accurately understanding the process, measures the performance of business units against reality (Darzi et al., 2023). This comprehensive framework handles prerequisite recognition steps, including monitoring and cleaning information system data to discover the current state of the process and examine it from various angles. The main objective of this paper was to develop a framework for improving the purchasing process based on process mining. This study presented a framework for process improvement proposals based on implementation, knowledge extraction from the process, discovery of unexpected and hidden relationships, and identification of bottlenecks in the purchasing process using process mining techniques.

In another study, Khoshkhoy Nilash et al. (2025) proposed a methodological framework based on process mining and data mining to analyze fixed capital facility processes. Using event data from an active bank in Iran, this research extracted the actual process, identified bottlenecks and frequent activities, and analyzed various process variants. Additionally, it examined the roles of the most involved branches and employees, as well as the data features affecting the reduction of facility payment times. In the data mining section, facility payment times were predicted and various methods were compared. Ultimately, by analyzing event data and identifying deviations, an improved process was extracted.

Norouzi and Yalveh (2025) examined studies conducted in the field of process mining within organizations. The development trend of process mining research indicates that in the 2010s, articles focused more on theoretical foundations and initial applications, while in the mid-decade, the development of methods and practical applications in various industries gained attention. The 2020s saw the use of artificial intelligence and machine learning for more precise data analysis. Recent research has focused on more innovative areas such as information security, maturity model development, and the use of modern tools in this domain.

An article aimed to introduce a novel method called BDPR (Bottleneck Detection, Prediction, and Recommendation), which uses process mining techniques to detect, predict, and offer operational solutions for process bottlenecks (Piest et al., 2021). This method is designed not only to identify bottlenecks but also to predict their future occurrence and recommend improvement actions, providing operational support for process management. To demonstrate its capabilities, the method was applied in a case study in the transport and logistics sector. The results show that, despite limitations in current process mining tools for prediction and recommendation, this method can serve as a foundation for improving performance and operational decision-making in organizational processes and for guiding the selection and development of process mining tools.

In another paper, authors combined process mining methods and value streams to analyze data from an information management system, applying this approach to data provided by a specific manufacturing system (Rudnitckaia et al., 2022). This paper used process mining algorithms to discover a descriptive process model, which served as a primary basis for further analysis. Concurrently, modern bottleneck analysis techniques were described, and two new, comprehensible bottleneck detection methods (Time Lag and Confidence interval methods) were discussed, along with their advantages. The obtained results can subsequently be adapted for other big data sources and industry-compatible information management systems.

Mohammadi et al. (2023) focused on the practical features of process mining—namely process model discovery, performance analysis, and bottleneck identification—and investigated the billing process for healthcare services provided by a local hospital. The results showed that this process consists of five main activities with the highest frequency. Furthermore, registering a new request to check the insurance type was identified as a bottleneck. Redesigning this path could have a significant impact on process efficiency.

In their article, Fang and Yu (2024) sought to develop a data-driven method for identifying and measuring production bottlenecks in Industry 4.04.04.0 systems. In this study, the authors used a combination of event data integration, process mining, and physics-based factory analysis to identify and quantify constraining activities. The research methodology comprised three main stages: first, data integration and cleaning of multi-source data; second, process mining to extract the actual process map and visually identify bottlenecks; third, digital imitation and calculation of activity indices based on factory physics concepts to determine constraining activities. The results demonstrated that this approach can accurately identify and quantify constraining activities and serve as an effective tool for improving productivity and planning production operations in industrial environments. This method is flexible and implementable in various systems to optimize manufacturing setups.

Another study investigated how to execute a process mining project in a family-owned Small and Medium Enterprise (SME) active in the agri-food sector, focusing on the challenges faced at each project stage to extract the most suitable process that eliminates all sources of waste and bottlenecks (Laghouag et al., 2024). This study applied process mining to a production process using the lifecycle methodology alongside Lean and quality management tools, such as the Fishbone diagram, Pareto chart, and Overall Equipment Effectiveness (OEE). Analyzing the results using Disco and ProM tools provided clues regarding the organizational and technical causes of production process inefficiencies. First, it was determined that the company faced equipment availability issues. Then, implementing the LLL lifecycle method enabled the identification of five critical causes. An action plan to eliminate these causes was proposed to the company's managers. In another study, reinforcement learning algorithms were used for process optimization tasks. Q-learning and Deep Q-network (DQN) techniques were employed to identify the optimal path. This was designed by constructing a reward matrix tailored to each method, which placed bottlenecks in absorbing states (Soliman et al., 2025).

A review of the theoretical foundations and research background shows that process mining, by leveraging actual data recorded in information systems, is a powerful tool for discovering actual process models, identifying deviations, and providing improvement solutions. Previous studies, particularly in the banking services and lending processes domains, have confirmed the efficacy of this approach in reducing cycle times, improving productivity, and identifying bottlenecks.

However, a significant portion of existing research has focused either on process discovery or on deviation identification, and less attention has been paid to combining performance analysis and bottleneck identification in an integrated manner—especially in real-world scenarios using well-known datasets such as the BPI Challenge 2012. In this research, relying on the frameworks proposed in the literature and utilizing process mining tools, a practical model is presented to discover the actual lending process, identify and quantify bottlenecks, and analyze key performance indicators. The research methodology of this study is based on event data analysis, process modeling, and performance evaluation, using a data-driven approach, as detailed in the following section.

Method

This study employed a quantitative method using data obtained from the BPI Challenge 2012. This research falls under the positivist paradigm, and, in terms of its objective, it is classified as applied research. Furthermore, because it examines data related to a specific period, it is a cross-sectional study. The methodology of this study consists of seven steps, which are briefly explained below:

Step 1: Data Preparation and Cleaning. This stage involves collecting event data from information systems and preparing it for analysis. Process mining data must include at least three key elements: a Case ID to distinguish between different cases, an Activity to indicate the step or action performed, and a Timestamp to determine the sequence of events. In this step, incomplete or inconsistent data is identified and corrected, and supplementary attributes, such as roles or human resources, are added if necessary. The objective of this phase is to ensure data quality and integrity for a more accurate analysis.

Step 2: Process Discovery. In this step, the actual process model is extracted from the event data using process mining techniques. Process mining tools can reconstruct the sequence of activities and provide a graphical representation of the workflow. This discovered model reflects the true behavior of the system and can reveal discrepancies with the designed or expected models. The primary goal of this stage is to identify frequent paths and understand the variations in process execution.

Step 3: Performance Analysis. This phase is dedicated to examining the Key Performance Indicators (KPIs) associated with the process. Among the most important indicators are the total processing time (cycle time), the waiting time between activities, and the successful throughput rate of various paths. Performance analysis enables the identification of process steps that consume the most time or cost, making them suitable candidates for improvement.

Step 4: Bottleneck Analysis. The objective of this step is to identify activities or transitions that cause delays or congestion in the process. Bottlenecks are typically characterized by high waiting times or a dense accumulation of cases. By providing heat maps or calculating time metrics, process mining tools can highlight the areas with the greatest negative impact on overall process efficiency. Accurate identification of these points serves as a basis for proposing corrective actions.

Step 5: Human Resource Analysis. In this stage, the interaction of human resources and their role in executing the process is examined. Resource analysis can include measuring employee workload, the time spent on each activity, or the collaboration patterns between organizational units. This analysis helps identify imbalances in task allocation, over-reliance on specific individuals, and areas that lead to decreased resource productivity.

Step 6: Deviation and Conformance Analysis. This step compares the actual model extracted from the data with a pre-designed or reference model. It is also possible to evaluate the conformance of the entire process against a few highly frequent paths. The goal is to assess the degree of compliance of the actual process execution with expected rules, procedures, or models. Deviations may include unauthorized paths, repeated activities, or skipped steps. Identifying these instances allows organizations to find the root causes of problems and implement necessary controls.

Step 7: Providing Improvement Proposals and Continuous Monitoring. After identifying weaknesses and bottlenecks, the findings from the previous steps are transformed into managerial insights. In this stage, improvement opportunities are divided into three main categories: automation of manual activities, optimization of resource allocation, and redesign of the process flow. The ultimate goal of this step is to provide practical solutions to increase efficiency, reduce costs, and improve the customer experience. Subsequently, to evaluate the effectiveness of the changes, KPIs must be continuously monitored. Process mining tools enable the creation of live dashboards that let managers monitor process performance in real time and sustain the continuous improvement cycle. This step ensures that the modifications are not merely temporary and become part of the organization’s permanent process management approach (Mohammadi et al., 2023).

Results

Based on the outlined research methodology, we apply the aforementioned steps to the target dataset and conduct appropriate analyses to achieve the desired results.

Step 1: Data Preparation and Cleaning

The data used in this study were extracted from the Business Process Intelligence (BPI) Challenge 2012 dataset. This dataset was retrieved from the official BPI Challenge repository in the standard XES format. It records the actual events of the loan application process at a Dutch financial institution, covering the complete lifecycle from initial submission to final decision (approval, rejection, or cancellation). Although newer BPI Challenge datasets exist, most of them focus on domains other than loan processing. BPI Challenge 2012 was selected because it provides a complete end-to-end loan application process and is well aligned with the objectives of this study.

This data file contains 13,087 loan application cases and approximately 262,200 events recorded between October 2011 and March 2012. Each event has a set of attributes, including the activity name indicating the specific step performed in the process, the exact date and time of the event, the event lifecycle stage (e.g., started, completed, scheduled), the resource executing the event (employee or system), and the requested loan amount for each case.

The first step is dedicated to data preparation. The goal of this phase is to enhance data quality and consistency to ensure the accuracy of results in the discovery and performance analysis stages. In this step, the original XES file was first examined. Since certain attributes, such as the loan amount, were initially assigned at the event level, the file was modified to allocate this attribute to the case (application) level. The events for each application were sorted based on their timestamps to reconstruct the actual sequence of activity execution. Subsequently, incomplete data or entries lacking an activity name or timestamp were identified and removed. For analysis purposes, the activity names were translated into their Persian equivalents. Additionally, the event date and time formats were standardized to ensure error-free processing in the process mining tools. Furthermore, consecutive duplicate activities recorded within a short time interval in some instances were considered data noise and merged. At the end of this step, a cleaned and unified dataset was ready to enter the process discovery phase.

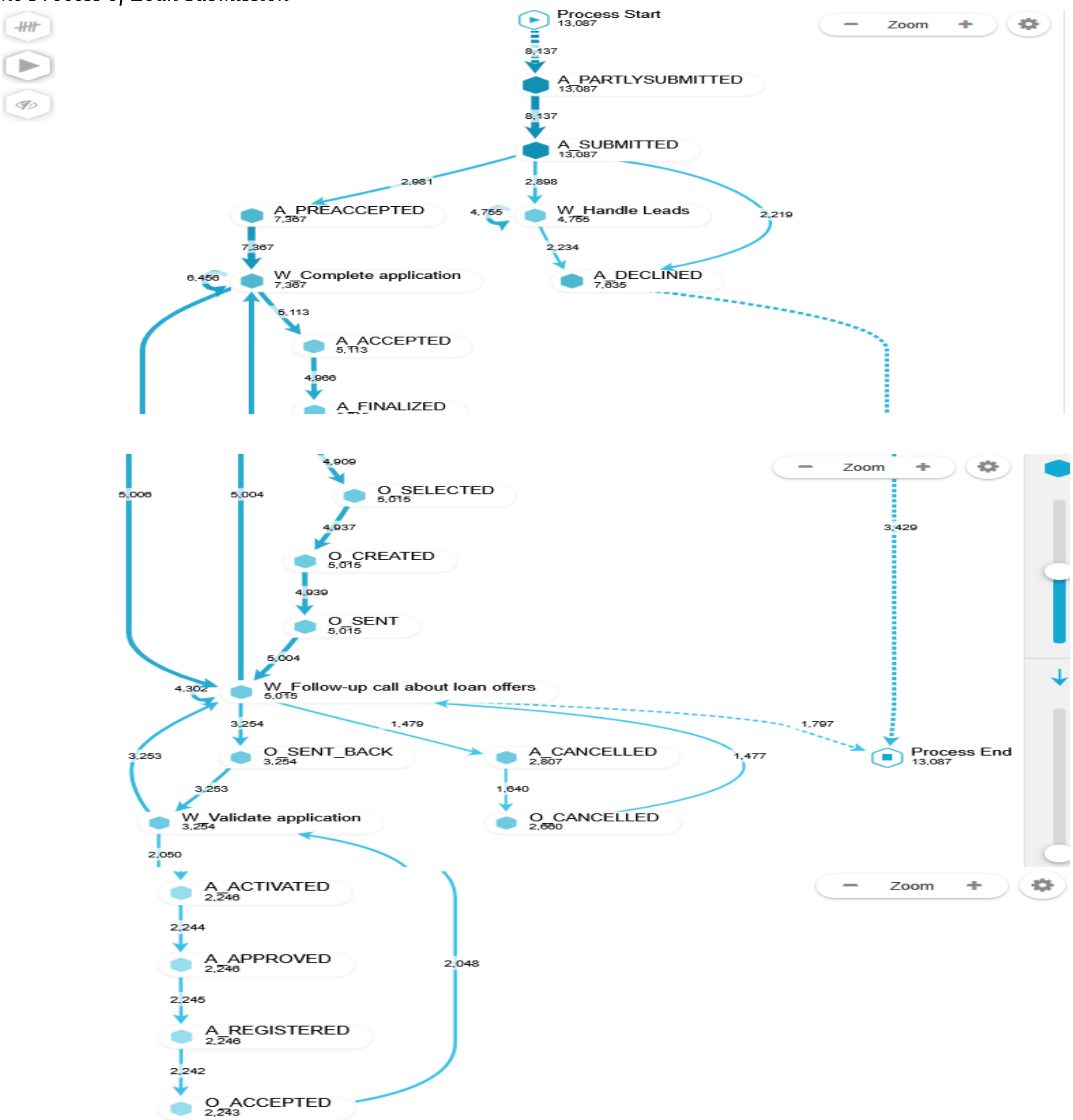
Step 2: Process Discovery

Following data preparation, the next phase was process discovery. The objective of this step is to reconstruct the process model based on real data and display the primary and deviant flows to provide a transparent picture of how the lending process is actually executed.

For this purpose, the Celonis process mining software was utilized. Using the Process Explorer in Celonis, the actual loan application process model was reconstructed. As Figure 1 shows, the process begins with the “Application Submission” stage and ultimately ends with either “Approval” or “Rejection”. The process model was visualized as an activity flow graph, with edge thickness representing the frequency of cases passing through and color intensity indicating the average time spent on or between activities. This visual representation enables the identification of high-frequency points, deviant paths, and interactions among sub-processes, serving as the foundation for the performance analyses in the subsequent step.

Figure 1

The Process of Loan Submission



Data analysis within the Celonis environment revealed that the bank loan application process possesses a very high degree of variation and complexity. While in many organizational processes, one or two main paths typically cover more than half of the cases, here, the three most frequent paths account for only 26%, 15%, and 4% of total applications, respectively, as shown in Table 1. This implies that more than half of the applications have flowed through various other paths, each representing a minor share of the total cases. The existence of such high dispersion in the paths indicates that the actual execution of the process involves numerous deviations and exceptions. These diverse paths primarily stem from factors such as requests for complementary documents, routing files back to previous stages for review, and the repetition of evaluation activities. Analyzing these paths indicates that a significant portion of the total processing time is due to these deviations and added complexities.

Therefore, a key finding of this analysis is that the loan application process requires a high level of standardization and simplification. Reducing the number of deviant paths and directing cases as much as possible toward the main paths can increase transparency, reduce processing time, and improve the customer experience.

Table 1

High-Frequency Paths of the Loan Application Process

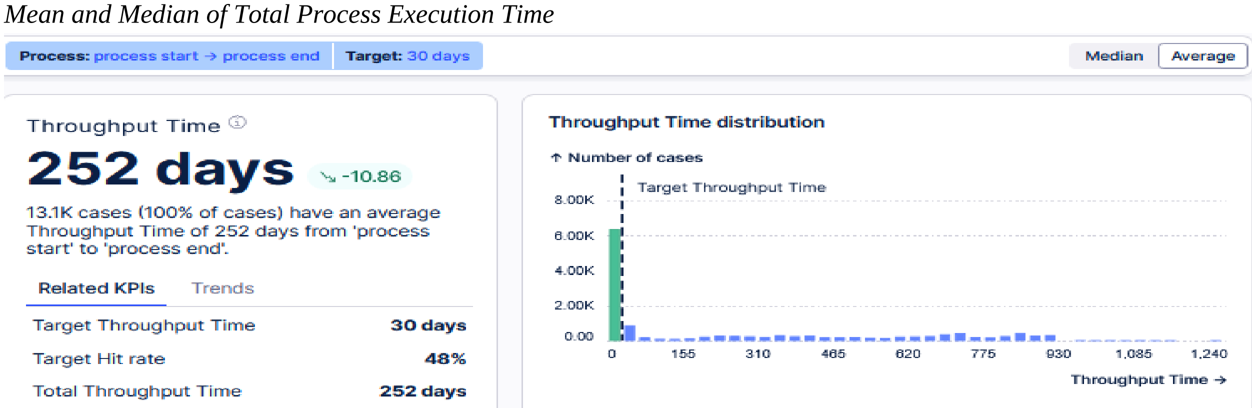
Row	Path	Coverage %	Number of Requests	Average Time
1	Loan Application Submitted → Loan Application Partially Submitted → Loan Application Rejected	26%	3429	0 days
2	Loan Application Submitted → Loan Application Partially Submitted → Lead Handling (2) → Loan Application Rejected → Lead Handling	15%	2019	0 days
3	Loan Application Submitted → Loan Application Partially Submitted → Lead Handling (2) → Loan Application Pre-Accepted → Application Completion (2) → Loan Application Rejected	4%	520	30 days

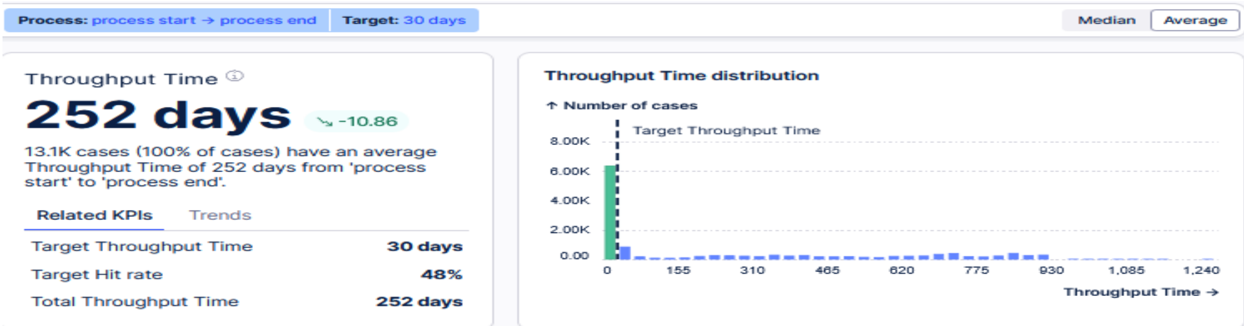
Step 3: Performance Analysis

In the third step, the performance of the lending process was examined with a focus on cycle time and waiting times between activities. As shown in Figure 2, the average total execution time of the process is 252 days, nd its median is 303 days. This significant difference between the mean and median indicates that a large number of cases with very long cycle times have skewed the average toward higher values.

Figure 2

Mean and Median of Total Process Execution Time





Furthermore, based on Table 2, comparing the performance of cases resulting in application approval versus rejection reveals that:

- Approved cases take an average of 18.19 days (≈436 hours) to complete.
- Rejected cases take an average of only 0.11 days (≈2.8 hours).

These findings indicate that although the rejection process is executed very quickly, the approval process requires multiple stages such as application completion, credit evaluation, and offer creation/submission, resulting in significantly more time spent.

Table 2

Average Time of Approved and Rejected Cases

Status	Average Duration (days)	Average Duration (hours)	Count
Application Approval	18.19	436.59	2955
Application Rejection	0.11	2.87	5719

In addition, as presented in Table 3, analyzing the relationships between activities showed that the longest waiting times occur in infrequent paths; this includes the transition from “Application Validation” to “Contract Information Editing” with an average of 30.68 days, and the transition from “Contacting Incomplete Files” to “Contract Information Editing” with an average of 14.16 days. Conversely, highly frequent paths such as “Application Completion → Application Completion” (15.26% of events with an average of 0.55 days) and “Offer Follow-up → Offer Follow-up” (14.48% of events with an average of 1.57 days), despite accounting for a large share of the total events, are executed much faster.

Table 3

Average Waiting Time for Relationships Between Activities

Relationship	Average Waiting Time (days)	Count	Percentage
Application Validation → Contract Information Modification	30.68	4	000
Follow-up on Incomplete Applications → Contract Information Modification	14.16	1	000
Contract Information Modification → Follow-up on Loan Offers	4.08	1	000
Application Completion → Follow-up on Loan Offers	3.1	5015	2.01
Follow-up on Loan Offers → Application Validation	2.58	3208	1.29
Follow-up on Loan Offers → Contract Information Modification	1.97	222	000
Follow-up on Loan Offers → Follow-up on Loan Offers	1.57	36084	14.48
Contract Information Modification → Application Validation	0.59	2	000
Application Completion → Application Completion	0.55	38004	15.26
Fraud Assessment → Fraud Assessment	0.47	367	0.15

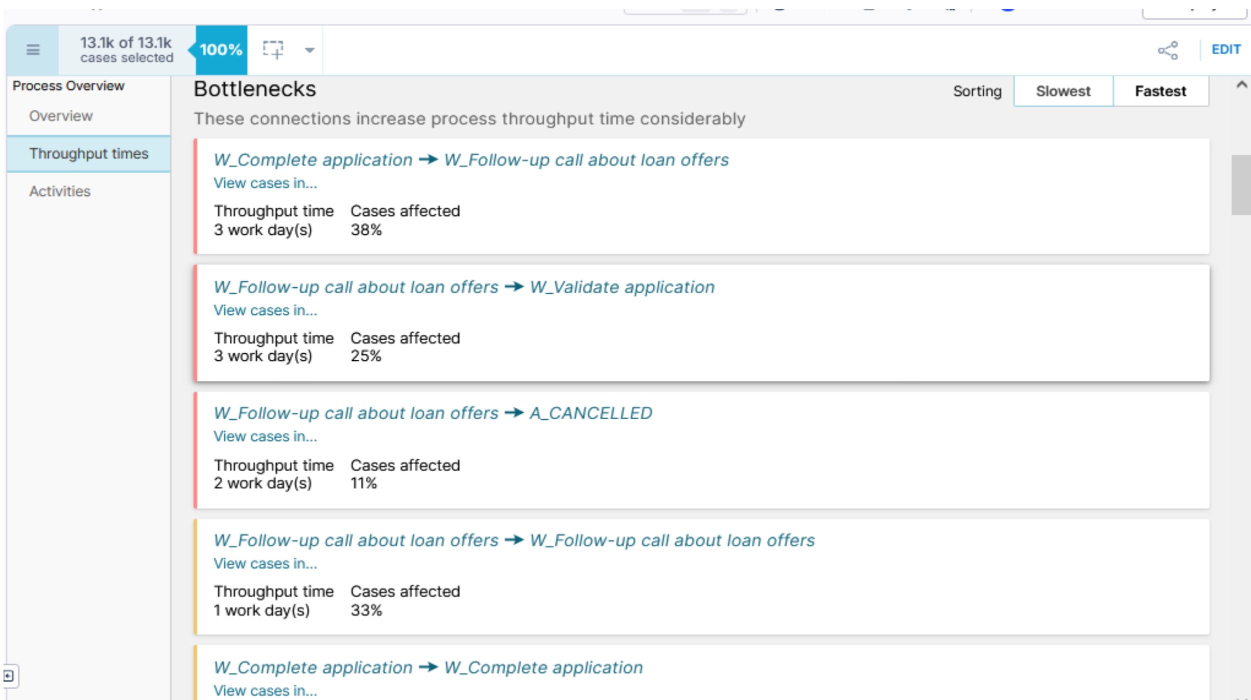
Overall, the performance analysis indicated that the process has a skewed time distribution; a limited number of long-cycle cases have inflated the overall average. Rejected cases are processed faster, but this apparent efficiency is accompanied by a reduced success rate. High-frequency activities are managed in short durations, whereas the primary bottlenecks occur in low-frequency, highly time-consuming activities. These results provide an appropriate foundation for identifying process bottlenecks in the fourth step.

Step 4: Bottleneck Analysis

The bottleneck section in Celonis provides a list of connections (from one activity to the next) that have the greatest impact on increasing the total process time. Based on the output shown in Figure 3, the top four connections. For each connection, the associated cases were examined and examples of the paths leading to them were extracted to investigate potential root causes (e.g., resource shortages, the need for supplementary documents, or repeated reviews). This analysis demonstrates that instead of focusing solely on a single isolated activity, the key connections between activities (e.g., "Application Completion → Follow-up on Loan Offers") must be targeted to achieve the greatest reduction in overall processing time.

Figure 3

Bottlenecks Visualization in Celonis



The list of bottlenecks is shown in Table 4.

Table 4

List of Bottlenecks

Relationship	Cycle Time (days)	Percentage of Cases
Application Completion → Follow-up on Loan Offers	3	38%
Follow-up on Loan Offers → Application Validation	3	25%
Follow-up on Loan Offers → Loan Application Cancelled	2	11%
Follow-up on Loan Offers → Follow-up on Loan Offers	1	33%

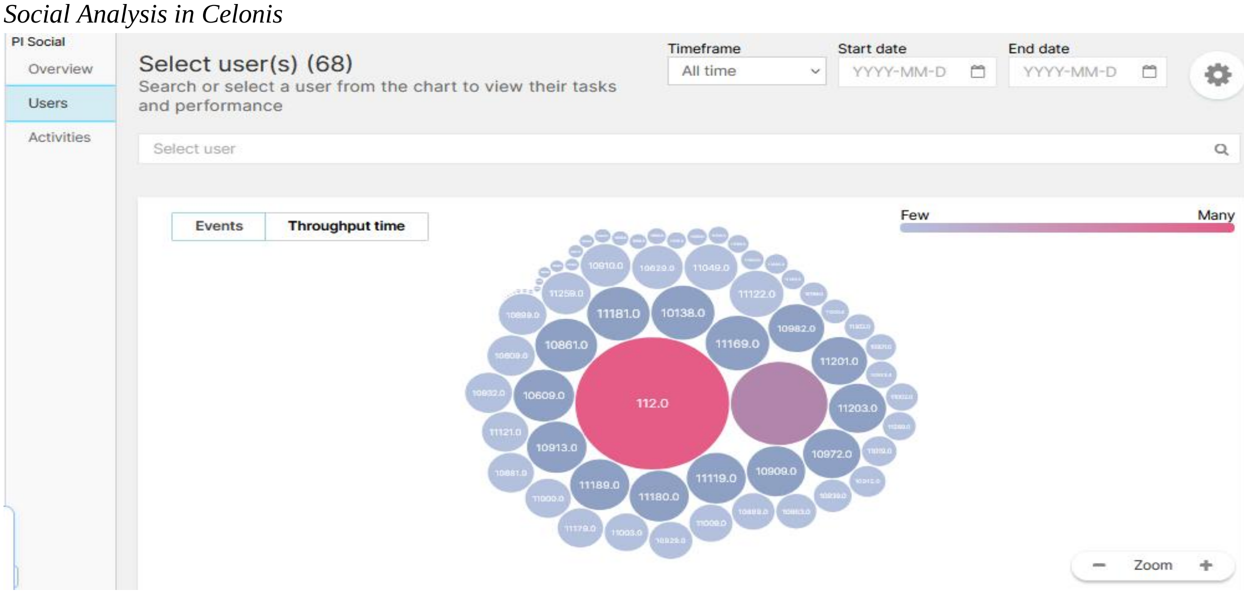
Step 5: Human Resource Analysis

In this section, the distribution of lending process activities among users was examined. The results of the social analysis in the Celonis environment indicate that 68 users were involved in the process. As shown in Figure 4, the volume of activities is unevenly distributed among users, so that some users bear a significantly higher workload, while others participate in only a limited portion of the activities.

For instance, a user with the ID 112.0 has recorded the highest volume of events and is located at the center of the process network. This indicates a high concentration of tasks for this user and the risk of a human bottleneck in the event of a disruption in their performance. In contrast, other users are positioned on the periphery of the network and account for a smaller share of the workload. This pattern suggests that the lending process has a high degree of centralization regarding human resource allocation. On the one hand, such a situation can facilitate coordination and accelerate decision-making, but on the other hand, it carries the risk of creating dependency on key personnel and increasing operational risk. Therefore, the redistribution of activities and the implementation of automation mechanisms can balance the workload among users and reduce dependence on a limited number of key users.

Figure 4

Social Analysis in Celonis



Step 6: Deviation and Conformance Analysis

In the sixth step, the conformance of the lending process with the standard model was evaluated. Since a reference or standard process model was not available, process conformance was assessed against the top 5 most frequent paths, and subsequently, activities that should not be considered discrepancies were excluded from the list. Ultimately, 16 instances were identified as acceptable deviations, and 20 types of discrepancies were retained. The results showed that only 59% of the cases were fully compliant with the process model, while 41% contained discrepancies, as illustrated in Figure 5. A more detailed analysis of the discrepancies revealed that the most frequent violations pertained to the execution of undesired or out-of-sequence activities. Specifically:

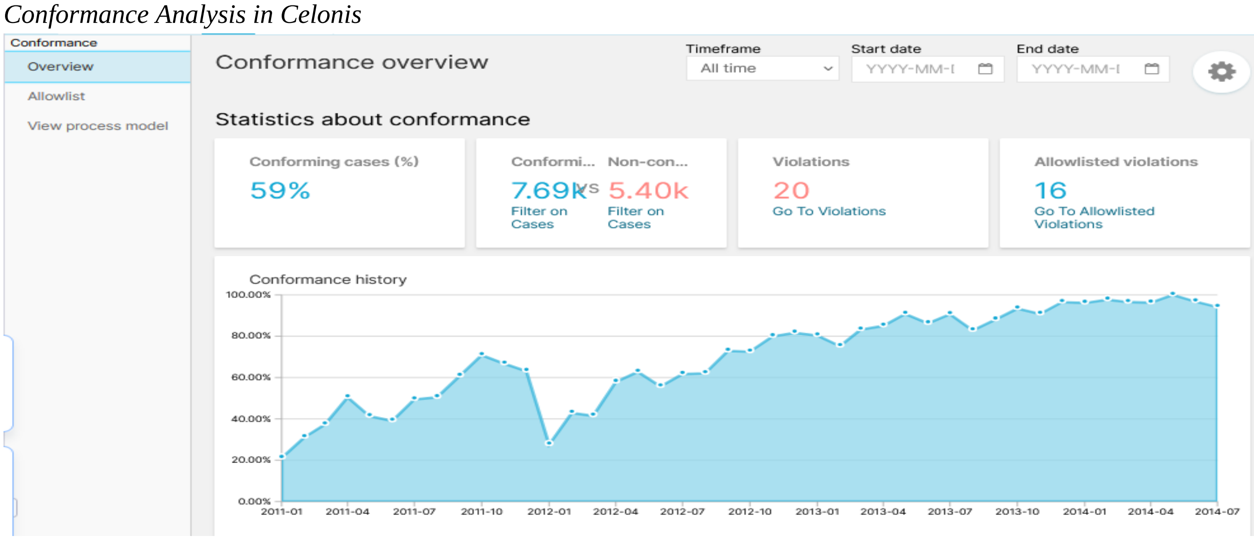
- The **Offer Follow-up** activity occurred as an undesired activity in 3,254 cases (25%), increasing the average cycle time by 532 days and adding an average of 36.4 extra steps per case.
- The **Contract Information Editing** activity was recorded as a discrepancy in 2,660 cases (20%), leading to a cycle time increase of 551 days and 34.9 additional steps.
- The **Contacting Incomplete Files** activity was also repeated outside the standard pattern in 1,647 cases (13%), increasing the cycle time by an average of 573 days.
- Furthermore, the execution of the **Application Rejection** activity was recorded as a discrepancy in 802 cases (6%), which added an average of 513 days to the loan cycle time.

Reviewing the conformance history indicated that the level of process compliance in the early years (2011) was below 30%, but it gradually reached approximately 80% in the years 2013–2014. This trend demonstrates a relative improvement in process standardization over time, although the overall conformance level (59%) remains significantly below the desired state.

Overall, the findings suggest that process deviations not only increase the number of processing steps but also directly and significantly prolong cycle time. Therefore, reducing repetitive activities such as offer follow-ups and frequent contract information editing can meaningfully improve process performance. It is recommended that the level of process conformance be enhanced through standardizing the main paths, utilizing digital checklists, and automating administrative activities.

Figure 5

Conformance Analysis in Celonis



Step 7: Improvement Recommendations and Continuous Monitoring

Based on the analyses conducted in the previous stages, a comprehensive set of recommendations to improve the lending process is proposed. As identified in the performance analysis (Step 3), the mean cycle time of the process is 252 days, with a median of 31 days, indicating the presence of highly protracted outlier cases. A significant portion of these delays stems from the “Application Validation” and “Application Completion” stages. Therefore, it is recommended to optimize these stages through automated document verification, the integration of smart credit scoring systems, and the establishment of strict Service Level Agreements (SLAs) to prevent excessive process prolongation.

In Step 4, the primary bottlenecks were identified in the transitions “Offer Follow-up→ Application Validation” and “Application Completion → Loan Application Registration.” With average delays of 62 and 34 days, respectively, these paths have the greatest negative impact on process efficiency. To mitigate this issue, implementing systemic controls for automated document completion checks and generating automated alerts for users during delayed stages are recommended. Furthermore, redesigning the sequence of certain activities could minimize unnecessary back-and-forth interactions between departments.

According to the human resources analysis (Step 5), the high concentration of activities among a limited number of users elevates the risk of human bottlenecks and processing delays. To address this vulnerability, intelligent task redistribution through automated allocation mechanisms, cross-training of employees, and increased overall automation are suggested to ensure workload balance and process stability.

As observed in Step 6, only 59% of the cases conformed to the standard paths, with activities such as “Offer Follow-up” and “Contract Information Editing” exhibiting the highest deviation rates. In this regard, utilizing digital checklists, defining permissible paths within the system, and enforcing real-time process controls are recommended to increase conformance rates and eliminate redundant activities.

To ensure the sustainability of these improvements, designing management dashboards based on Key Performance Indicators (KPIs)—including cycle time, conformance rate, application success rate, and individual user workload—is proposed. These dashboards must be updated automatically and in real time to facilitate rapid, data-driven decision-making.

Overall, implementing these measures can lead to a drastic reduction in cycle time, increased process conformance, a balanced distribution of human resources, and enhanced customer satisfaction. Conversely, continuous monitoring of KPIs ensures the sustainability of organizational learning and the ongoing improvement of the lending process.

Discussion and Conclusion

This study aimed to analyze performance and identify bottlenecks in a loan application process using real-world event data from the BPI Challenge 2012. To achieve this, following data preparation and process modeling in process mining environments, several analytical stages were executed, including data description, path reconstruction, performance analysis, bottleneck identification, human resource evaluation, and process conformance checking.

The findings revealed that:

- The mean process cycle time is 252 days, with a median of 31 days, indicating the presence of exceptional cases with excessively long cycle times.
- The most frequent process paths rapidly lead to application rejection or cancellation, whereas the successful path (culminating in a contract) accounts for only 6%-8% of all cases.
- The primary process bottlenecks were identified in the application completion and validation stages, which significantly inflate the cycle time.
- The human resources analysis demonstrated that a major portion of the workload is handled by a limited number of key users, potentially creating human bottlenecks and increasing operational risk.
- The process conformance rate against the reference model was only 59%, indicating that 41% of cases contained discrepancies, such as repetitive activities and out-of-sequence task execution.

Based on these findings, a suite of strategic solutions was proposed, encompassing reducing repetitive activities, optimizing human resource allocation, standardizing primary paths, accelerating time-consuming stages with smart technologies, and deploying real-time monitoring tools. These interventions can collectively drive improved efficiency, higher conformance rates, and an elevated banking customer experience.

From an academic perspective, this research demonstrated that process mining provides an accurate, data-driven representation of the actual state of organizational processes, transparently revealing opportunities for improvement. For future research, it is recommended to expand the proposed framework by using datasets from other banks and financial processes, and to integrate more advanced methodologies, such as process simulation and machine learning, to enhance its generalizability.

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The authors declare no conflicts of interest

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data Availability Statement

Data will be available on request from the authors.

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