

Enterprise workflow efficiency assessment through process analytics and performance measurement frameworks

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Abstract

The effectiveness of organizational operations largely depends on the efficiency of business workflows and the ability to monitor process performance across interconnected enterprise functions. This study presents a process analytics framework for evaluating workflow efficiency through quantitative performance measurement and enterprise data analysis. The proposed methodology integrates workflow mapping, process cycle-time analysis, throughput evaluation, and resource utilization assessment to identify operational bottlenecks and inefficiencies. Enterprise information systems serve as the primary source of process data, enabling structured analysis across multiple business functions. Statistical techniques and performance indicators are used to measure workflow consistency, task completion rates, and operational productivity. The framework is validated using simulated enterprise process environments and comparative benchmarking against conventional workflow assessment approaches. Findings indicate that systematic process analytics can significantly improve operational visibility, support performance improvement initiatives, and facilitate evidence-based decision-making. The proposed framework offers organizations a scalable method for continuously evaluating and improving workflow effectiveness across enterprise environments.

Keywords: Business Process Management; Enterprise Workflow; Process Analytics; Process Mining; Workflow Efficiency; Performance Measurement; Workflow Assessment; Enterprise Information Systems; Operational Performance; Decision Support.

1. Introduction

Enterprise organizations increasingly depend on integrated business workflows to coordinate activities across procurement, finance, manufacturing, logistics, human resources, and customer service. The widespread adoption of enterprise information systems, including Enterprise Resource Planning (ERP), Customer Relationship Management (CRM), Human Resource Management Systems (HRMS), and workflow management platforms, has enabled organizations to collect large volumes of operational process data. These data provide opportunities to analyze workflow execution, identify operational inefficiencies, and evaluate organizational performance. Consequently, improving enterprise workflow efficiency has become an important objective for organizations seeking to increase

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productivity, optimize resource utilization, reduce operational delays, and support evidence-based managerial decision-making.

1.1. Background and Motivation

Business Process Management (BPM), process mining, and process analytics have introduced systematic approaches for examining workflow behavior using enterprise event logs. These technologies allow organizations to monitor workflow execution, identify bottlenecks, and measure operational performance more effectively than traditional manual assessment methods. Despite these advances, many organizations still evaluate workflow performance using isolated indicators such as execution time or task completion rates, which provide only a partial view of workflow effectiveness. Since enterprise workflows involve multiple interconnected activities, evaluating performance through a single metric may overlook process deviations, resource inefficiencies, and workflow inconsistencies that influence overall operational performance.

1.2. Problem Statement

Existing workflow assessment approaches often focus on individual aspects of enterprise operations, such as process mining, workflow monitoring, or performance measurement, without integrating these techniques into a unified evaluation framework. This fragmented approach limits the ability of organizations to obtain a comprehensive understanding of workflow performance across interconnected business functions. As a result, operational bottlenecks, inefficient resource allocation, and workflow deviations may remain undetected until they significantly affect organizational productivity. These limitations indicate the need for an integrated framework capable of combining process analytics with quantitative performance measurement to support continuous enterprise workflow assessment.

1.3. Research Objective and Contributions

This study proposes an Enterprise Workflow Efficiency Assessment Framework that integrates workflow modeling, process analytics, and quantitative performance measurement into a unified evaluation approach. The framework utilizes enterprise event data to analyze workflow execution, calculate multiple performance indicators, and support continuous operational assessment within enterprise environments. To demonstrate its applicability, the framework is evaluated using a simulation-based enterprise environment and compared with a conventional workflow assessment approach.

The main contributions of this research are summarized as follows:

- Development of an integrated framework for enterprise workflow efficiency assessment using workflow modeling, process analytics, and performance measurement.
- Introduction of a multidimensional evaluation model based on Process Cycle Time, Throughput, Task Completion Rate, Resource Utilization, Workflow Consistency, Waiting Time, and Process Compliance.
- Validation of the proposed framework through simulation-based experimental evaluation.
- Provision of a structured decision-support approach for continuous workflow monitoring and operational improvement.

1.4. Paper Organization

The remainder of this paper is organized as follows. Section II reviews previous studies on business process management, process analytics, workflow performance measurement, and enterprise workflow assessment. Section III presents the proposed framework. Section IV describes the research methodology, while Section V explains the experimental design and performance evaluation procedure. Section VI presents the experimental results and discussion. Finally, Section VII concludes the paper and outlines directions for future research.

2. Literature Review

Enterprise workflow efficiency has been extensively studied through Business Process Management (BPM), process mining, process analytics, and performance measurement. The increasing availability of enterprise event data has enabled organizations to evaluate workflow execution using data-driven analytical techniques rather than traditional manual assessment methods. This section reviews previous research on enterprise workflow management, process analytics, workflow performance measurement, and identifies the research gap addressed in this study.

2.1. Enterprise Workflow Management

Enterprise workflows coordinate business activities across multiple organizational functions to achieve operational objectives. Business Process Management (BPM) provides a systematic approach for designing, executing, monitoring, and improving these workflows throughout their lifecycle [11], [20]. Process-oriented organizations generally achieve better operational transparency, resource utilization, and process consistency than function-oriented organizations [18]. Recent studies have also shown that BPM capabilities support digital transformation by improving organizational adaptability and decision-making [14]. Collectively, these studies demonstrate that enterprise workflow management has evolved into a data-driven discipline where enterprise information systems continuously provide operational data for workflow monitoring and performance assessment.

2.2. Process Analytics and Process Mining

Process analytics has become an essential approach for evaluating workflow behavior using enterprise event logs. Process mining techniques support process discovery, conformance checking, and performance analysis by extracting knowledge directly from workflow execution records [10]. Recent developments have expanded process mining from traditional process discovery to object-centric process analysis and structured project methodologies, allowing more comprehensive evaluation of complex enterprise workflows [1]–[3], [9].

Predictive process analytics further extends workflow evaluation by applying machine learning techniques to forecast future process behavior and identify potential bottlenecks before they occur [5]. Applications of process mining have been successfully reported across manufacturing, healthcare, finance, logistics, and public administration, demonstrating its effectiveness in improving workflow visibility and operational analysis [7], [12]. The quality of event logs remains a critical factor for analytical accuracy, making data preprocessing and conformance checking essential components of enterprise workflow analysis [8], [16]. More recent studies have also integrated process analytics with business process intelligence and artificial intelligence to improve enterprise workflow evaluation and decision support [17], [21]–[23].

2.3. Performance Measurement Frameworks

Performance measurement provides objective evidence for evaluating enterprise workflow effectiveness. Modern organizations assess workflow performance using multiple indicators, including process cycle time, throughput, task completion rate, waiting time, resource utilization, workflow consistency, and process compliance, rather than relying on a single operational metric [13]. Performance measurement systems also support organizational learning by providing continuous feedback for process improvement [19]. Recent studies have combined process analytics with multi-criteria decision analysis and intelligent workflow evaluation to improve operational performance assessment and managerial decision-making [6], [15], demonstrating the value of integrating analytical techniques with quantitative performance indicators.

2.4. Research Gap

Previous research has made significant contributions to BPM, process mining, workflow monitoring, and performance measurement. However, most studies address these areas independently or focus on specific application domains [1], [3], [7], [12]. Although recent work has incorporated predictive analytics and AI-assisted BPM [5], [14], [22], limited attention has been given to developing a unified framework that integrates workflow modeling, process analytics, and comprehensive performance measurement for enterprise-wide workflow assessment. To address this limitation, this study proposes an Enterprise Workflow Efficiency Assessment Framework that combines these components into a structured evaluation model for continuous workflow monitoring and evidence-based decision-making.

3. Proposed Framework

This section presents the proposed Enterprise Workflow Efficiency Assessment Framework, which integrates enterprise workflow modeling, process analytics, and quantitative performance measurement into a unified workflow evaluation approach. The framework is designed to identify operational inefficiencies using enterprise event data and objective performance indicators. It supports continuous workflow monitoring by converting operational process records into measurable information that assists managers in evaluating workflow performance and identifying opportunities for process improvement.

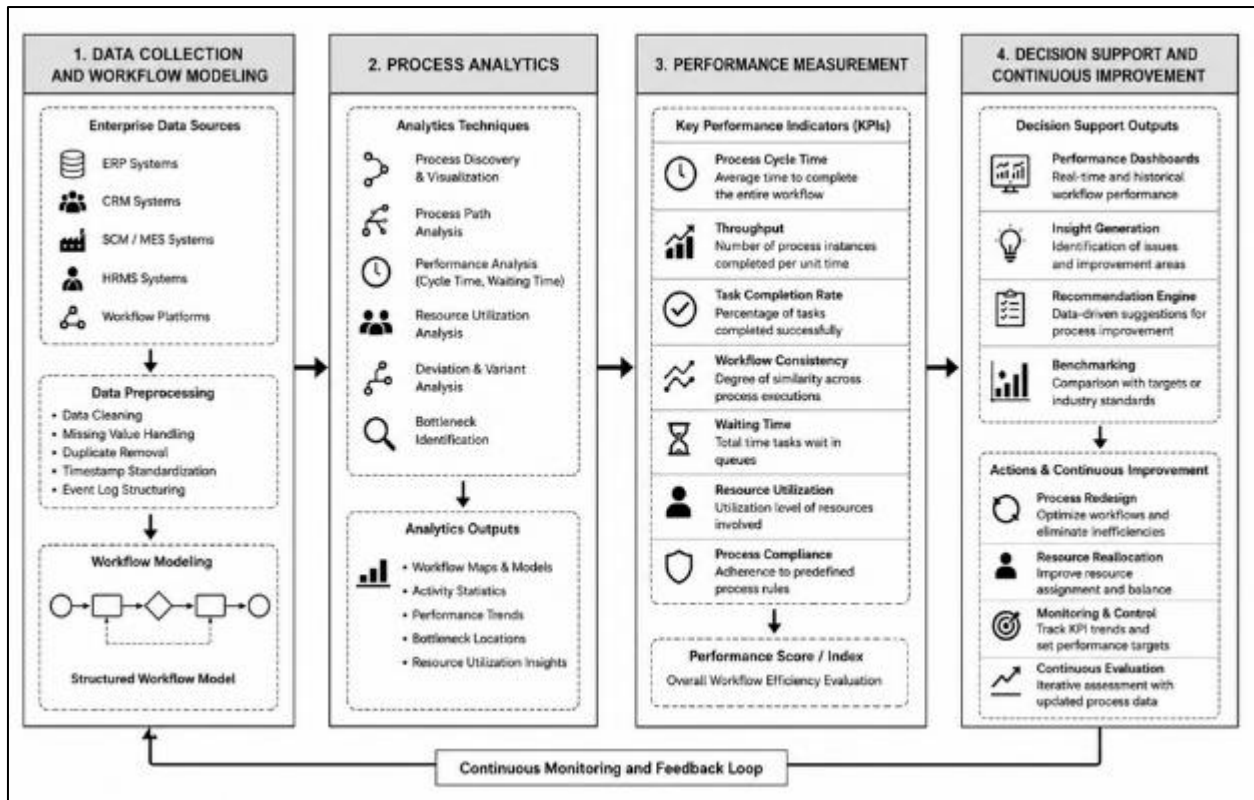


Figure 1 Proposed Enterprise Workflow Efficiency Assessment Framework

The proposed framework consists of four interconnected components that operate sequentially. Enterprise process data are first collected from organizational information systems and transformed into workflow models. Process analytics techniques are then applied to examine workflow execution patterns and identify operational bottlenecks. Performance indicators are calculated to measure workflow efficiency, while the final component summarizes analytical findings to support managerial decision-making and continuous workflow improvement.

3.1. Framework Overview

The framework begins with enterprise process data generated by operational systems such as Enterprise Resource Planning (ERP), Customer Relationship Management (CRM), Human Resource Management Systems (HRMS), Manufacturing Execution Systems (MES), and workflow management platforms. These systems continuously record workflow activities, execution timestamps, user interactions, and resource allocation information. After data preprocessing, workflow activities are organized into structured process models that represent the sequence and relationships among business tasks.

3.2. Enterprise Workflow Analytics Process

The workflow analytics component evaluates process execution using enterprise event logs. Process data are analyzed to determine workflow paths, execution frequencies, waiting times, process deviations, and resource utilization patterns. The analytical results provide visibility into workflow behavior and help identify activities that contribute to delays, redundant operations, or inefficient resource allocation. Comparative analysis across multiple workflow instances also supports the identification of recurring operational problems and long-term performance trends.

3.3. Performance Measurement Model

Workflow efficiency is assessed using multiple quantitative performance indicators rather than a single evaluation metric. The proposed framework measures process cycle time, throughput, task completion rate, workflow consistency, waiting time, resource utilization, and process compliance. These indicators provide complementary views of operational performance and allow organizations to evaluate workflow effectiveness from different perspectives. The measurement procedures and mathematical formulations of these indicators are presented in the Research Methodology section.

3.4. Decision Support Mechanism

The final component translates analytical results into practical information for organizational decision-making. Performance reports identify workflow bottlenecks, inefficient resource utilization, and process deviations that require corrective action. Managers can use these findings to redesign workflows, improve resource allocation, and monitor performance over time. By repeating the assessment process as new workflow data become available, the proposed framework supports continuous performance evaluation and promotes data-driven improvement across enterprise operations.

4. Research Methodology

This section describes the methodology adopted to develop and evaluate the proposed Enterprise Workflow Efficiency Assessment Framework. The methodology combines workflow modeling, process analytics, quantitative performance measurement, and comparative evaluation within a simulated enterprise environment. Enterprise workflow data are processed through sequential analytical stages to assess operational performance and identify workflow inefficiencies. The overall methodology is designed to provide a repeatable approach that can be applied across different enterprise environments.

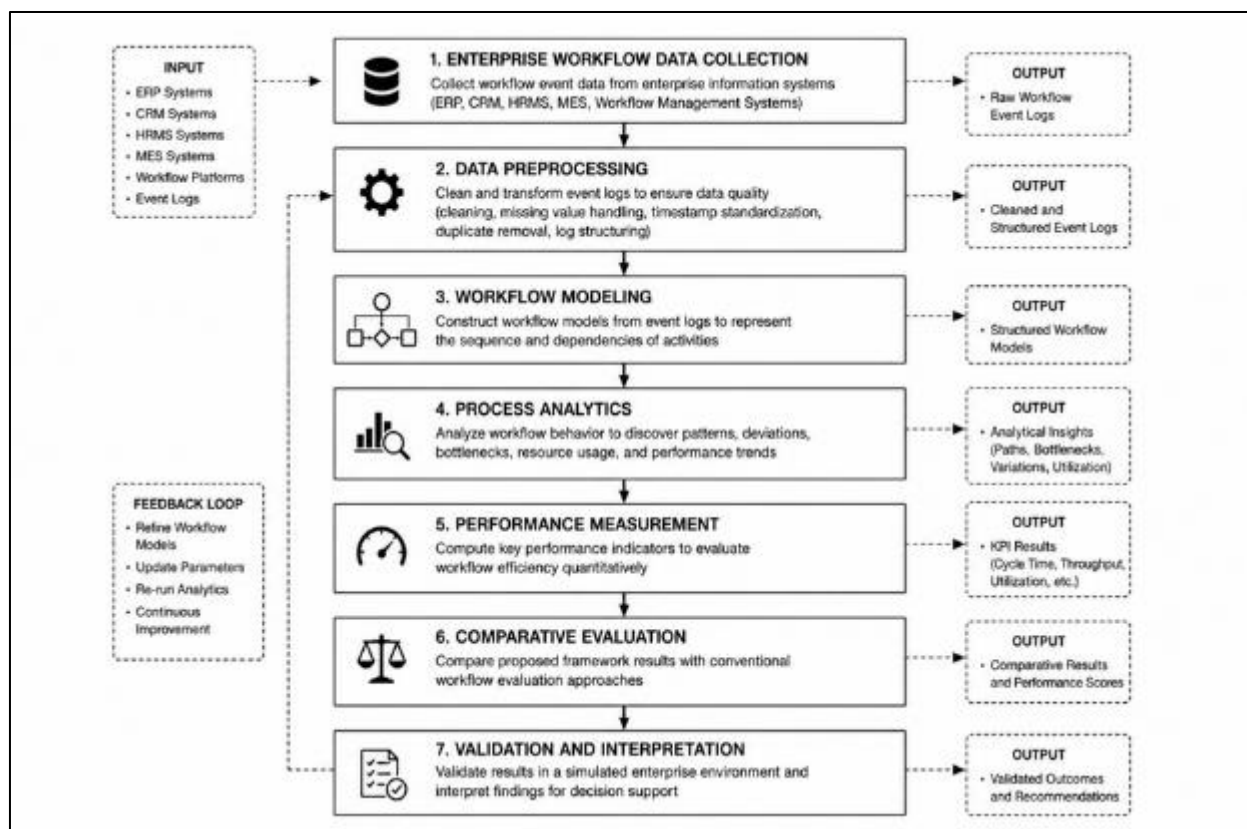


Figure 2 Research Methodology Flowchart

4.1. Research Design

This study adopts a quantitative, framework-based research design. A simulated enterprise workflow environment is used to evaluate the proposed framework because it allows controlled observation of workflow behavior under different operational conditions. The methodology focuses on objective performance evaluation using workflow execution data rather than subjective user perception. Enterprise workflows are represented as structured sequences of business activities, and process performance is assessed using predefined analytical metrics.

4.2. Workflow Modeling and Data Preparation

Enterprise workflow data are assumed to originate from operational information systems such as ERP, CRM, HRMS, and workflow management platforms. Each workflow instance consists of activity identifiers, timestamps, process identifiers, resource information, and execution status.

Before analysis, workflow records undergo preprocessing to improve data quality. This stage includes duplicate record removal, missing value handling, timestamp standardization, and event log organization. The cleaned event logs are then transformed into structured workflow models that describe the sequence of business activities and process dependencies.

4.3. Process Analytics Procedure

The workflow models are analyzed to evaluate operational behavior. Process analytics identifies workflow execution paths, activity frequencies, waiting times, bottlenecks, and resource utilization patterns. Comparative analysis of multiple workflow instances is performed to detect recurring inefficiencies and process deviations.

The analytical procedure also examines workflow consistency by comparing observed execution sequences with the expected workflow model. This analysis supports the identification of abnormal workflow behavior that may reduce operational efficiency.

4.4. Performance Measurement

Workflow efficiency is evaluated using quantitative performance indicators that represent different aspects of enterprise operations.

Table 1 Performance Indicators Used for Workflow Efficiency Assessment

Performance Indicator	Description	Measurement Unit	Performance Objective
Process Cycle Time (PCT)	Total time required to complete a workflow instance from initiation to completion.	Minutes / Hours	Lower values indicate faster workflow execution.
Throughput (TP)	Number of workflow instances completed within a specified time period.	Instances per Day	Higher values indicate greater operational productivity.
Task Completion Rate (TCR)	Percentage of assigned tasks completed successfully.	Percentage (%)	Higher values indicate better workflow execution reliability.
Resource Utilization (RU)	Degree to which available organizational resources are utilized during workflow execution.	Percentage (%)	Higher values indicate more effective resource usage.
Workflow Consistency (WC)	Degree of similarity between observed workflow execution and the expected workflow model.	Percentage (%)	Higher values indicate more stable and standardized workflows.
Waiting Time (WT)	Total idle time between two consecutive workflow activities.	Minutes / Hours	Lower values indicate fewer operational delays.
Process Compliance (PC)	Percentage of workflow instances executed according to predefined business rules and policies.	Percentage (%)	Higher values indicate better process governance and compliance.

- **Process Cycle Time**

$$PCT = T_{end} - T_{start}$$

where T_{end} represents workflow completion time and T_{start} represents workflow initiation time.

- **Throughput**

$$TP = \frac{N}{t}$$

where N is the number of completed workflow instances during time period t .

- **Task Completion Rate**

$$TCR = \frac{N_c}{N_t} \times 100$$

where N_c denotes completed tasks and N_t represents total assigned tasks.

- **Resource Utilization**

$$RU = \frac{T_u}{T_a} \times 100$$

where T_u is the resource utilization time and T_a is the total available resource time.

4.5. Framework Validation

The proposed framework is validated using a simulated enterprise workflow consisting of multiple business processes executed under different operational conditions. Performance indicators obtained from the proposed framework are compared with those generated using a conventional workflow assessment approach based primarily on execution time monitoring. Comparative evaluation focuses on the framework's ability to identify workflow bottlenecks, measure operational performance, and provide decision-support information for continuous process improvement.

The results obtained from this validation are presented and discussed in the following section.

5. Experimental Design and Performance Evaluation

This section describes the experimental design adopted to evaluate the proposed Enterprise Workflow Efficiency Assessment Framework. A simulated enterprise environment was developed to represent common organizational workflows involving multiple business functions. The evaluation procedure measures workflow performance using predefined performance indicators and compares the proposed framework with a conventional workflow assessment approach. The objective is to determine the framework's capability to identify workflow inefficiencies and support quantitative performance evaluation.

5.1. Simulated Enterprise Environment

The experimental evaluation was conducted using a simulated enterprise workflow environment that represents routine business operations across multiple organizational departments. The simulation includes business processes commonly performed in procurement, inventory management, finance, human resource management, and customer service. Each workflow consists of a sequence of interconnected activities executed by different organizational resources. Enterprise event logs record activity identifiers, timestamps, resource assignments, workflow status, and process completion information.

The simulated environment provides a controlled setting for evaluating workflow behavior while avoiding the confidentiality limitations associated with real organizational datasets. Multiple workflow instances are generated under different operational conditions to represent variations in workload, resource availability, and process execution.

5.2. Experimental Configuration

The proposed framework evaluates workflow performance using standardized process analytics procedures. Workflow event logs are preprocessed before analysis to remove incomplete records, duplicated events, and inconsistent timestamps. The cleaned datasets are then transformed into structured workflow models for subsequent analytical processing.

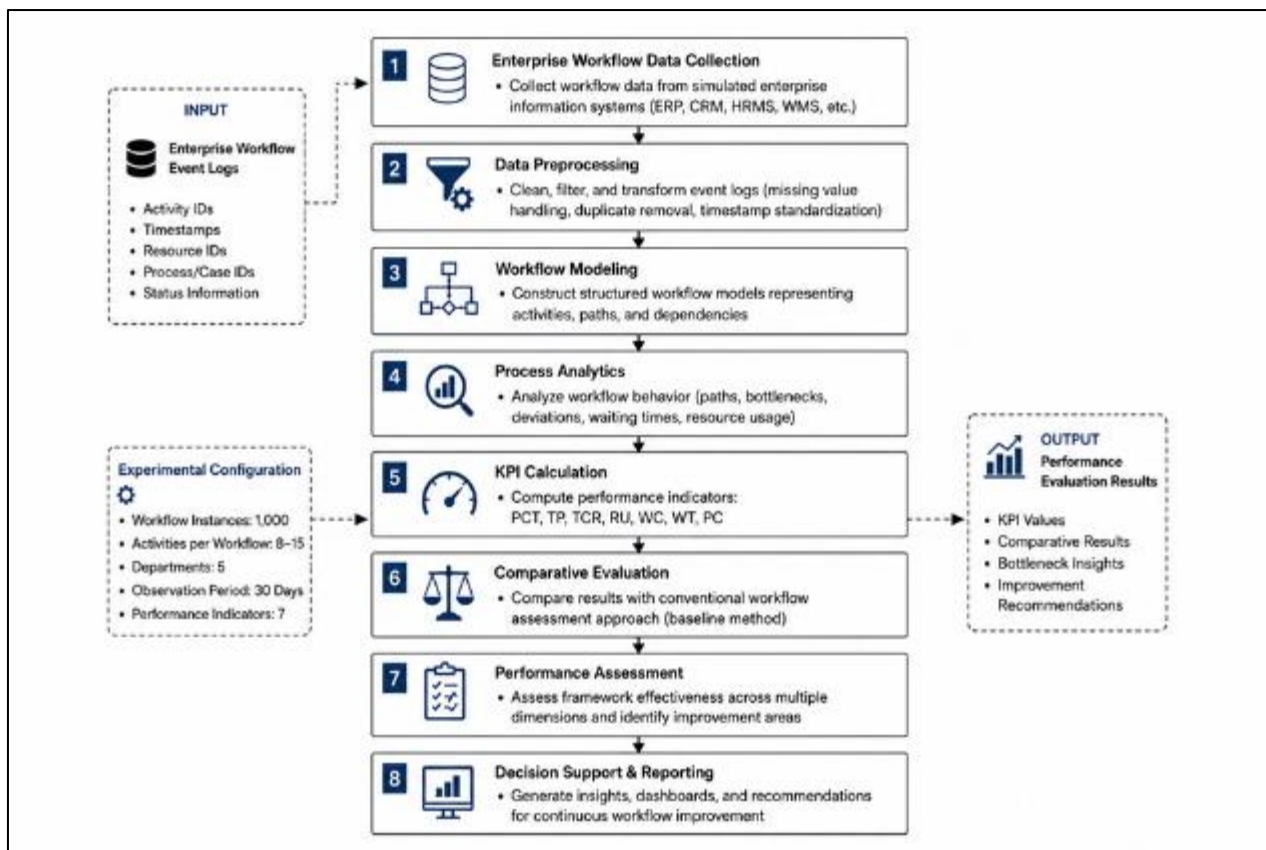
Table 2 Experimental Configuration Parameters

Parameter	Configuration
Enterprise Environment	Simulated Multi-Department Organization
Organizational Functions	Procurement, Inventory, Finance, HR, Customer Service
Workflow Instances	1,000
Activities per Workflow	8–15
Observation Period	30 Days
Data Source	Simulated Enterprise Event Logs
Performance Indicators	7
Evaluation Method	Comparative Performance Analysis

The selected configuration provides sufficient workflow diversity for evaluating process behavior under different operational scenarios while maintaining consistency across experimental observations.

5.3. Performance Evaluation Procedure

The evaluation follows a structured sequence consisting of workflow data collection, event log preprocessing, workflow modeling, process analytics, performance measurement, comparative assessment, and performance reporting. During each evaluation cycle, workflow execution data are analyzed to identify bottlenecks, process deviations, waiting times, resource utilization patterns, and workflow consistency.

**Figure 3** Experimental Performance Evaluation Procedure

The calculated performance indicators include Process Cycle Time (PCT), Throughput (TP), Task Completion Rate (TCR), Resource Utilization (RU), Workflow Consistency (WC), Waiting Time (WT), and Process Compliance (PC). These

indicators provide complementary measures of workflow efficiency and enable comprehensive evaluation of enterprise operations.

5.4. Comparative Evaluation Strategy

The effectiveness of the proposed framework is assessed by comparing its analytical capabilities with those of a conventional workflow assessment approach. The conventional method primarily evaluates workflow performance using execution time and task completion statistics, whereas the proposed framework integrates workflow analytics with multiple quantitative performance indicators.

Comparative evaluation focuses on four aspects: workflow visibility, bottleneck identification, performance measurement accuracy, and decision-support capability. Workflow visibility refers to the framework's ability to represent process execution across organizational functions. Bottleneck identification measures its capability to detect activities that contribute to workflow delays. Performance measurement accuracy is evaluated through the calculation of multiple workflow indicators, while decision-support capability is assessed by examining how analytical results assist managers in identifying opportunities for workflow improvement.

The experimental results obtained from this evaluation are presented and analyzed in the following section.

6. Results

This section presents the performance evaluation results obtained from the simulated enterprise workflow environment and discusses the effectiveness of the proposed Enterprise Workflow Efficiency Assessment Framework. The evaluation focuses on the framework's ability to analyze workflow behavior, measure operational performance, identify process inefficiencies, and support managerial decision-making. The analytical outcomes are compared with those obtained using a conventional workflow assessment approach to demonstrate the advantages of integrating process analytics with quantitative performance measurement.

6.1. Workflow Performance Evaluation

The simulated enterprise environment generated multiple workflow instances representing routine business operations across procurement, inventory management, finance, human resources, and customer service. After preprocessing and workflow modeling, the proposed framework successfully analyzed workflow execution patterns and calculated the performance indicators defined in the methodology.

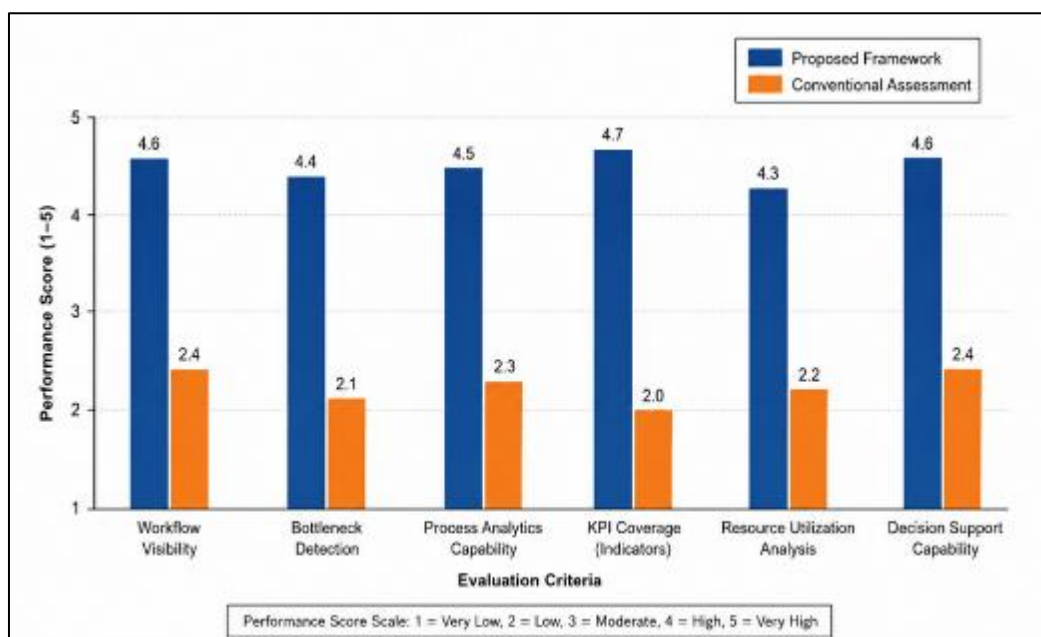


Figure 4 Comparative Performance Evaluation of the Proposed Framework and Conventional Workflow Assessment

The analytical results showed that the framework was capable of identifying process bottlenecks, excessive waiting times, workflow deviations, and inefficient resource allocation. Unlike the conventional assessment approach, which primarily relied on workflow completion statistics, the proposed framework provided a comprehensive evaluation by simultaneously measuring Process Cycle Time (PCT), Throughput (TP), Task Completion Rate (TCR), Resource Utilization (RU), Workflow Consistency (WC), Waiting Time (WT), and Process Compliance (PC).

The comparative analysis indicated that the proposed framework provides greater visibility into workflow execution by integrating multiple operational indicators rather than relying on a single performance measure. This multidimensional assessment allows managers to identify the root causes of workflow inefficiencies instead of observing only the final operational outcomes.

6.2. Comparative Performance Analysis

The comparison between the proposed framework and the conventional workflow assessment approach demonstrates clear differences in analytical capability. The conventional approach primarily measures workflow completion time and task execution statistics, whereas the proposed framework evaluates workflow performance from multiple operational perspectives.

Table 3 Comparative Evaluation of Workflow Assessment Approaches

Evaluation Criterion	Conventional Assessment	Proposed Framework
Workflow Visibility	Limited	Comprehensive
Bottleneck Identification	Partial	Comprehensive
Process Analytics	Basic	Advanced
Performance Indicators	Limited KPIs	Multiple Integrated KPIs
Resource Utilization Analysis	Limited	Comprehensive
Workflow Consistency Assessment	Not Supported	Supported
Decision Support Capability	Moderate	High
Continuous Performance Monitoring	Limited	Supported

As summarized in Table III, the proposed framework provides broader analytical coverage by integrating workflow modeling, process analytics, and quantitative performance measurement into a unified evaluation process. The additional analytical information enables managers to detect operational problems earlier and prioritize improvement initiatives based on objective evidence.

7. Discussion

The experimental evaluation demonstrates that combining process analytics with multiple performance indicators provides a more complete assessment of enterprise workflow efficiency than conventional monitoring approaches. The framework not only evaluates workflow outcomes but also examines process behavior throughout workflow execution. This capability allows organizations to identify operational bottlenecks, resource imbalances, and workflow deviations before they significantly affect organizational performance.

The results are consistent with previous studies emphasizing the importance of process mining and business process management for workflow analysis [1]-[3], [11], [12]. Similarly, the use of multiple performance indicators supports earlier research highlighting the role of quantitative performance measurement in evaluating business processes [13], [19]. Recent studies on intelligent business process management also suggest that integrating process analytics with advanced analytical techniques improves organizational decision-making and operational transparency [14], [15], [22].

Although the proposed framework demonstrates promising performance within the simulated enterprise environment, several limitations should be acknowledged. The experimental evaluation is based on simulated workflow data rather than real organizational datasets, and the framework has not yet been validated across different industrial sectors. Furthermore, the current framework evaluates workflow performance using predefined performance indicators and does not incorporate adaptive machine learning models for real-time optimization.

Future research may extend the proposed framework by integrating real enterprise event logs, predictive process analytics, and artificial intelligence techniques to support automated workflow optimization and continuous performance improvement in dynamic organizational environments.

8. Conclusion

This study proposed an Enterprise Workflow Efficiency Assessment Framework that integrates workflow modeling, process analytics, and quantitative performance measurement to evaluate workflow performance within enterprise environments. By combining workflow mapping, event log analysis, and multiple performance indicators, the framework provides a structured approach for identifying workflow inefficiencies and supporting continuous operational assessment.

The simulation-based evaluation demonstrated that the proposed framework offers more comprehensive workflow analysis than conventional assessment approaches by improving workflow visibility, bottleneck identification, and performance measurement across multiple organizational functions. The integration of Process Cycle Time, Throughput, Task Completion Rate, Resource Utilization, Workflow Consistency, Waiting Time, and Process Compliance provides a multidimensional view of workflow efficiency that supports evidence-based managerial decision-making.

This study is limited by the use of simulated enterprise data, and the framework has not yet been validated using real organizational datasets. Future research may evaluate the framework across different industries using real enterprise event logs and investigate the integration of predictive process analytics, machine learning, and real-time monitoring to support continuous workflow optimization and enterprise performance improvement.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

- [1] Augusto, A., Conforti, R., Dumas, M., La Rosa, M., Maggi, F. M., Marrella, A., Mecella, M., & Soo, A. (2021). Automated discovery of process models from event logs: Review and benchmark. *IEEE Transactions on Knowledge and Data Engineering*, 33(4), 1680–1698. <https://doi.org/10.1109/TKDE.2019.2953320>
- [2] Berti, A., & van der Aalst, W. M. P. (2022). Reviving process mining project methodology. *Algorithms*, 15(10), 357. <https://doi.org/10.3390/a15100357>
- [3] Berti, A., van Zelst, S. J., & van der Aalst, W. M. P. (2023). Object-centric process mining: Principles, applications, and challenges. *Computers in Industry*, 150, 103950. <https://doi.org/10.1016/j.compind.2023.103950>
- [4] Jöhnk, J., Weißert, M., & Wyrski, K. (2021). Ready or not, AI comes: An interview study of organizational AI readiness factors. *Business & Information Systems Engineering*, 63(1), 5–20. <https://doi.org/10.1007/s12599-020-00676-7>
- [5] Mehdiyev, N., Evermann, J., & Fettke, P. (2021). A multi-stage deep learning approach for business process prediction. *Decision Support Systems*, 146, 113546. <https://doi.org/10.1016/j.dss.2021.113546>
- [6] Ni, Z. (2025). Data-driven business process evaluation in commercial banks: Integrating process mining, social network analysis, and DEMATEL-AHP. *Systems*, 13(4), 256. <https://doi.org/10.3390/systems13040256>
- [7] Park, G., Song, M., & van der Aalst, W. M. P. (2022). Process mining in healthcare: A literature review and future directions. *Healthcare*, 10(2), 304. <https://doi.org/10.3390/healthcare10020304>
- [8] Suriadi, S., Andrews, R., ter Hofstede, A. H. M., & Wynn, M. T. (2021). Event log imperfection patterns for process mining: Towards a systematic framework. *Information Systems*, 95, 101624. <https://doi.org/10.1016/j.is.2020.101624>
- [9] van der Aalst, W. M. P., & Berti, A. (2023). Foundations of object-centric process analysis. *Software and Systems Modeling*, 22(4), 1315–1338. <https://doi.org/10.1007/s10270-023-01084-8>

- [10] van der Aalst, W. M. P. (2016). *Process mining: Data science in action* (2nd ed.). Springer. <https://doi.org/10.1007/978-3-662-49851-4>
- [11] Dumas, M., La Rosa, M., Mendling, J., & Reijers, H. A. (2018). *Fundamentals of business process management* (2nd ed.). Springer. <https://doi.org/10.1007/978-3-662-56509-4>
- [12] García, C. S., Meincheim, A., Faria Junior, E. R., Dallagassa, M. R., Sato, D. M. V., Carvalho, D. R., Santos, E. A. P., & Scalabrin, E. E. (2019). Process mining techniques and applications: A systematic mapping study. *Expert Systems with Applications*, 133, 260–295. <https://doi.org/10.1016/j.eswa.2019.05.003>
- [13] van Looy, A., & Shafagatova, A. (2016). Business process performance measurement: A structured literature review of indicators, measures, and metrics. *SpringerPlus*, 5, 1797. <https://doi.org/10.1186/s40064-016-3498-1>
- [14] Huy, P. Q. (2025). Unveiling how business process management capabilities foster dynamic decision-making for effectiveness of sustainable digital transformation. *Business Process Management Journal*, 31(8), 67–103. <https://doi.org/10.1108/BPMJ-06-2024-0467>
- [15] Bhaskar, H. L., Osama, M., & Reeta. (2025). Maximizing business process efficiency in Industry 4.0: A technological exploration of process mining tools. *SN Operations Research Forum*, 6(1). <https://doi.org/10.1007/s43069-025-00428-x>
- [16] Rozinat, A., & van der Aalst, W. M. P. (2008). Conformance checking of processes based on monitoring real behavior. *Information Systems*, 33(1), 64–95. <https://doi.org/10.1016/j.is.2007.07.001>
- [17] Grigori, D., Casati, F., Castellanos, M., Dayal, U., Sayal, M., & Shan, M.-C. (2004). Business process intelligence. *Computers in Industry*, 53(3), 321–343. <https://doi.org/10.1016/j.compind.2003.10.007>
- [18] Kohlbacher, M. (2010). The effects of process orientation: A literature review. *Business Process Management Journal*, 16(1), 135–152. <https://doi.org/10.1108/14637151011017985>
- [19] Neely, A. (2005). The evolution of performance measurement research: Developments in the last decade and a research agenda for the next. *International Journal of Operations & Production Management*, 25(12), 1264–1277. <https://doi.org/10.1108/01443570510633648>
- [20] Weske, M. (2019). *Business process management: Concepts, languages, architectures* (3rd ed.). Springer. <https://doi.org/10.1007/978-3-662-59432-2>
- [21] Stierle, M., Kraume, K., & Matzner, M. (2025). Process analytics: Data-driven business process management. *arXiv*. <https://doi.org/10.48550/arXiv.2512.20703>
- [22] Dumas, M., Fournier, F., Limonad, L., Marrella, A., Montali, M., Rehse, J.-R., Accorsi, R., Calvanese, D., De Giacomo, G., Fahland, D., Gal, A., La Rosa, M., Völzer, H., & Weber, I. (2023). AI-augmented business process management systems: A research manifesto. *ACM Transactions on Management Information Systems*, 14(1), Article 11. <https://doi.org/10.1145/3576047>
- [23] Jessen, U., & Fahland, D. (2024). WISE: Unraveling business process metrics with domain knowledge. *arXiv*. <https://doi.org/10.48550/arXiv.2410.04387>
- [24] Hasan, E. (2025). Big Data-Driven Business Process Optimization: Enhancing Decision-Making Through Predictive Analytics. *TechRxiv*. October 07, 2025. 10.36227/techrxiv.175987736.61988942/v1
- [25] Akhter, T. (2025, October 6). Algorithmic internal controls for SMEs using MIS event logs. *TechRxiv*. <https://doi.org/10.36227/techrxiv.175978941.15848264.v1>
- [26] Al Sany, S. M. A., Rahman, M., & Haque, S. (2025). ERP–MIS Integration for Intelligent Apparel Production Planning. *World Journal of Advanced Engineering Technology and Sciences*, 17(1), 145–156. <https://doi.org/10.30574/wjaets.2025.17.1.1387>
- [27] Rahman, F., Nahar, S., & Mim, M. A. (2026). Cloud-native enterprise resource management for multi-sector operations. *Global Journal of Engineering and Technology Advances*, 26(01), 126–141. <https://doi.org/10.30574/gjeta.2026.26.1.0012>
- [28] Sharmin, M., Rahman, M. A., Rohman, H., & Tumpa, S. A. (2026). Business operations monitoring through integrated management information systems. *International Journal of Science and Research Archive*, 19(3), 309–324. <https://doi.org/10.30574/ijrsra.2026.19.3.1097>

- [29] Akter, T. (2026, March 30). Design and implementation of intelligent KPI-based decision support systems for data-driven operations management in U.S. enterprises. *SSRN*. <https://doi.org/10.2139/ssrn.6496239>
- [30] Mim, M., & Akter, M. (2026, January 28). Integration of business intelligence dashboards in administrative decision making. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.6402899>
- [31] Khayyam, F. (2026). Design and implementation of generative artificial intelligence-driven automation for enterprise customer relationship management decision support systems. *Global Journal of Engineering and Technology Advances*, 27(2), 164–177. <https://doi.org/10.30574/gjeta.2026.27.2.0089>
- [32] Mirza, S. B., Islam, M. A., Tariq, F., & Shaik, M. H. (2026). Diagnostic analytics for enterprise reporting platforms. *Saudi Journal of Engineering and Technology*, 11(4), 247–256. <https://doi.org/10.36348/sjet.2026.v11i04.009>
- [33] Alam, M. J., Khayyam, F., Junaid, E., & Ahmed, M. (2026). Intelligent regulatory monitoring and audit trail information systems for enterprise risk and compliance management. *International Journal of Science and Research Archive*, 19(3), 283–295. <https://doi.org/10.30574/ijrsra.2026.19.3.1165>
- [34] Dukkupati, S. S. N. C., Junaid, E., Siddiki, A., & Khayyam, F. (2026). Scalable cloud-native microservices architecture for enterprise AI platforms: Reliability, security, and real-time distributed processing frameworks. *International Journal of Science and Research Archive*, 19(3), 296–308. <https://doi.org/10.30574/ijrsra.2026.19.3.1110>
- [35] Dukkupati, S. S. N. C. (2026, May 7). Design and performance evaluation of event-driven microservices for large-scale enterprise data processing. *SSRN*. <https://doi.org/10.2139/ssrn.6730598>
- [36] Nahar, S. (2025). Optimizing HR management in smart pharmaceutical manufacturing through IIoT and MIS integration. *World Journal of Advanced Engineering Technology and Sciences*, 17(03), 240–252. <https://doi.org/10.30574/wjaets.2025.17.3.1554>
- [37] Mim, M. M. A., Sharif, M. M., Rahman, F., & Nahar, S. (2026). AI-powered decision support systems for sustainable organizations. *International Journal of Scientific Research and Engineering Development (IJSRED)*, 9(1), 423–434. <https://doi.org/10.5281/zenodo.18454996>
- [38] Haque, S. (2025). The impact of automation on accounting practices. *IJSRED – International Journal of Scientific Research and Engineering Development*, 8(6), 2312–2323. <https://doi.org/10.5281/zenodo.18074324>
- [39] Al Sany, S. M. A. (2025). The role of data analytics in optimizing budget allocation and financial efficiency in startups. *IJSRED – International Journal of Scientific Research and Engineering Development*, 8(5), 2287–2297. <https://doi.org/10.5281/zenodo.17536325>
- [40] Akter, T., Afroje, S., Chokder, R., & Bhuiyan, M. I. H. (2026). Workforce productivity measurement models for service-oriented organizations. *Saudi Journal of Engineering and Technology*, 11(4), 257–265. <https://doi.org/10.36348/sjet.2026.v11i04.010>
- [41] Bhuiyan, M. I. H., Akter, T., Afroje, S., & Chokder, R. (2026). Operational risk indicators derived from customer interaction data in digital banking platforms. *Saudi Journal of Engineering and Technology*, 11(4), 266–275. <https://doi.org/10.36348/sjet.2026.v11i04.011>