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Process Intelligence for Compliance-Aware Project Governance in Digital Service Organizations

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Research Article

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Abstract

This study proposes a process intelligence approach for improving project governance in digital service organizations where operational efficiency, regulatory compliance, and stakeholder coordination are critical. The research develops a structured project governance model that integrates workflow mapping, KPI monitoring, requirements documentation, and compliance indicators to support systematic project health assessment. The proposed model evaluates project health using measurable variables, including requirement volatility, workflow delay, backlog priority, compliance exposure, and documentation completeness. A weighted Governance Performance Index (GPI) is employed to quantify governance performance and is defined as $G = w_1R + w_2K + w_3C + w_4D - w_5V$, where, R represents requirement clarity, K represents KPI alignment, C represents compliance readiness, D represents documentation quality, and V represents process volatility or disruption. The proposed framework is evaluated using a simulated workflow dataset representing project activities, process delays, requirements changes, backlog conditions, compliance exposure, and documentation status. Using a simulated workflow dataset, the evaluation illustrates how the GPI can consolidate multidimensional governance indicators into an interpretable project health measure and identify areas requiring managerial attention . The study contributes a structured and measurable process intelligence framework for supporting project governance and decision-making in banking, healthcare, real estate technology, and other service-based digital environments.

Keywords: Process Intelligence, Process Mining, Compliance Aware Project Governance, Digital Service Organizations, Enterprise Information Systems, Event Log Analytics, Compliance Management, Governance Analytics, Business Process Management, Decision Support Systems.

I. Introduction

Digital service organizations rely on enterprise information systems, workflow automation, and artificial intelligence (AI) to manage projects and business operations. These technologies generate large volumes of event log data that record process execution, resource allocation, and organizational activities. Process intelligence applies analytical methods to these data to evaluate business processes, monitor compliance, and support project governance. As regulatory requirements and project complexity continue to increase, organizations require governance models that combine operational monitoring with data driven decision support.

A. Background and Motivation

Recent research has examined artificial intelligence in project management, process mining for organizational process analysis, and compliance monitoring in process-aware information systems [1]-[3], [6]-[9]. Process mining reconstructs and analyzes actual process execution from event logs, while AI provides analytical and decision-support capabilities for project and organizational management [2], [6], [7]. Compliance monitoring adds a governance dimension through the identification and assessment of deviations from predefined regulatory or process requirements [3], [8], [13]. Together, these research areas provide a foundation for applying process intelligence to project governance in digital service organizations.

B. Problem Statement

Although previous research has made substantial contributions to artificial intelligence, process mining, and compliance management, these areas often address specific analytical, operational, or compliance functions [1]-[3], [6]-[9], [13], [14]. Organizational process-mining research has also reported limited attention to complex cross-system and service-oriented applications [7]. Consequently, there remains a need for an integrated framework that connects process intelligence, compliance assessment, governance analytics, and decision support at the project level. The absence of such integration can limit continuous project monitoring and the systematic evaluation of governance performance in digital service organizations.

C. Proposed Solution

This study proposes a Process Intelligence Framework for Compliance-Aware Project Governance in Digital Service Organizations. The framework integrates event-log analysis, process mining, compliance assessment, governance analytics, and AI-supported decision support within a unified architecture. The proposed approach evaluates project execution, identifies compliance deviations, and measures governance performance through quantitative indicators.

D. Contributions

This paper presents a Process Intelligence Framework for Compliance-Aware Project Governance in Digital Service Organizations. The framework integrates process mining, compliance assessment, governance analytics, and AI-supported decision support within a unified architecture. It defines quantitative indicators for evaluating process execution, compliance deviations, and project governance performance. The study also provides a systematic methodology covering data preparation, process intelligence analysis, governance assessment, and framework validation. The resulting framework supports project monitoring, compliance evaluation, and managerial decision support and provides a basis for further empirical research in digital service organizations.

E. Paper Organization

The remainder of this paper is organized as follows. Section II reviews the literature on process intelligence, process mining, compliance management, and enterprise governance. Section III presents the proposed methodology, including framework architecture, data preprocessing, analytical modeling, and validation procedures. Section IV discusses the experimental results and governance evaluation. Finally, Section V concludes the study and outlines directions for future research.

II. Literature Review

Process intelligence is an active research area in compliance management, project governance, and decision support for digital service organizations. Previous studies have examined artificial intelligence (AI), process mining, compliance management, digital governance, and enterprise information systems. Together, these studies provide the theoretical and technical background for data-driven governance frameworks.

A. Artificial Intelligence and Process Intelligence

Artificial intelligence supports project governance through decision support, risk assessment, resource analysis, and process-oriented analytics. Recent research on AI in project

management shows increasing use of AI for project-related planning, monitoring, and decision support [1], [2]. Process mining provides an empirical basis for process intelligence through the analysis of event logs and organizational process execution. Empirical research also indicates that process mining has been applied across organizational and service contexts, although complex cross-system and cross-organizational applications remain less represented [7]. These findings provide a foundation for integrating AI-supported analytics with process intelligence for project governance.

B. Process Mining and Compliance Management

Process mining uses event logs to reconstruct process execution, compare observed behavior with expected process models, and identify deviations from predefined process requirements [6], [7]. Compliance monitoring extends this analysis through systematic identification and assessment of deviations from regulatory, organizational, or process-specific requirements [8], [13]. Predictive compliance monitoring research has also examined the use of process-aware information systems to identify potential compliance problems before or during process execution [3]. Compliance patterns that incorporate data-related requirements provide an additional basis for evaluating compliance within information-system-supported processes [9]. Recent work in the banking sector also indicates the potential of process mining for addressing practical business process compliance challenges [14]. These studies support the use of process intelligence as a foundation for compliance-aware project governance.

C. Digital Governance and Enterprise Information Systems

Digital governance depends on reliable information management, process transparency, and continuous monitoring of organizational activities. Data governance research emphasizes the importance of structured data management for trustworthy AI-supported organizational systems [4]. Process mining research provides an additional mechanism for observing actual process execution and identifying deviations from expected process behavior [6], [7]. Organizational studies also show that process mining has potential across service-oriented and enterprise environments, while more complex cross-system applications remain comparatively limited [7]. These findings indicate that enterprise information systems can provide the operational data required for process intelligence, while governance mechanisms can use process-level evidence for compliance assessment, performance monitoring, and managerial decision support [8], [14].

D. Research Gap and Future Direction

The reviewed literature demonstrates substantial progress in artificial intelligence for project management, process mining for organizational process analysis, and compliance monitoring

for business processes [1]-[3], [6]-[9], [13], [14]. However, these research streams generally emphasize specific analytical or compliance functions rather than a unified governance framework that connects process execution data, compliance assessment, project-level governance indicators, and managerial decision support. Organizational process-mining research has also identified limited coverage of complex cross-system and service-oriented applications [7]. This indicates a research opportunity for a process intelligence framework that integrates event-log analysis, compliance monitoring, governance analytics, and AI-supported decision support within digital service organizations. The present stu

III. Methodology

This study adopts a sequential methodology to develop and evaluate a Process Intelligence Framework for Compliance-Aware Project Governance in Digital Service Organizations. The methodology includes research design, framework development, data collection, data preprocessing, process intelligence analysis, compliance assessment, governance evaluation, and validation. Each phase generates outputs that become inputs for the subsequent phase. This sequence provides a reproducible procedure for analyzing organizational event logs and evaluating project governance.

A. Research Design

The study employs the Design Science Research (DSR) methodology together with a quantitative analytical approach. The proposed framework integrates process mining, compliance monitoring, governance analytics, and AI-supported decision support within a single analytical environment. The research process begins with problem identification and literature review, followed by framework construction, data preparation, analytical modeling, validation, and result interpretation.

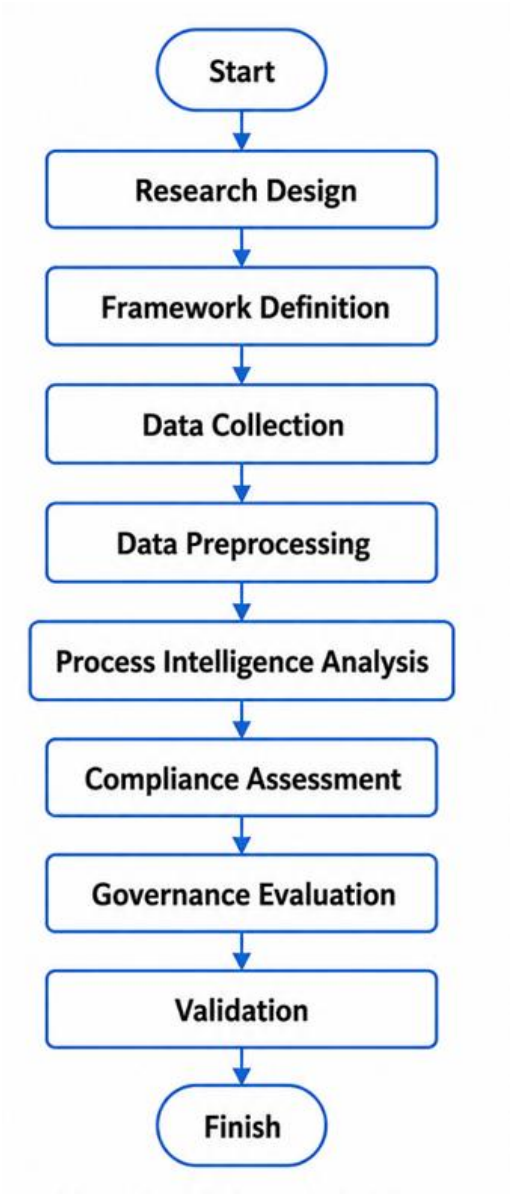


Fig.1 Overall Research Workflow**.**

B. Framework and System Architecture

The proposed framework contains six functional modules: data acquisition, preprocessing, process intelligence, compliance assessment, governance analytics, and decision support. Enterprise information systems provide operational event logs that are converted into standardized datasets before process mining analysis. The compliance module compares process execution with predefined organizational rules, while the governance module computes performance indicators and transfers the results to a decision support dashboard.

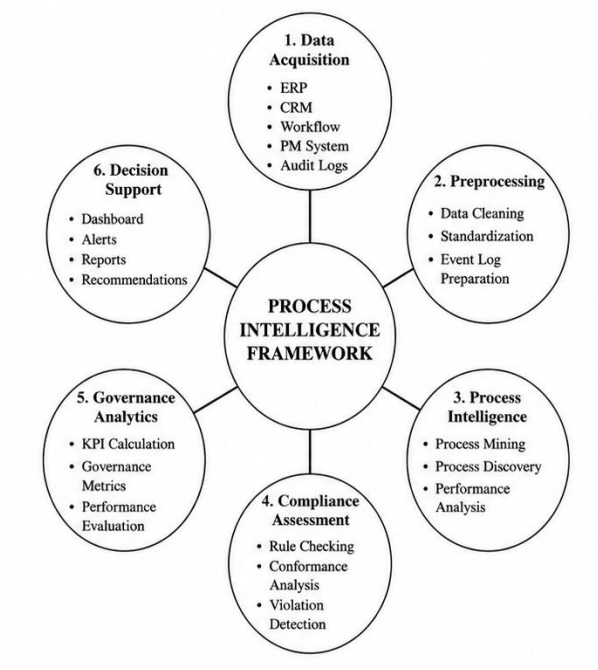


Fig.2 Proposed Process Intelligence Framework

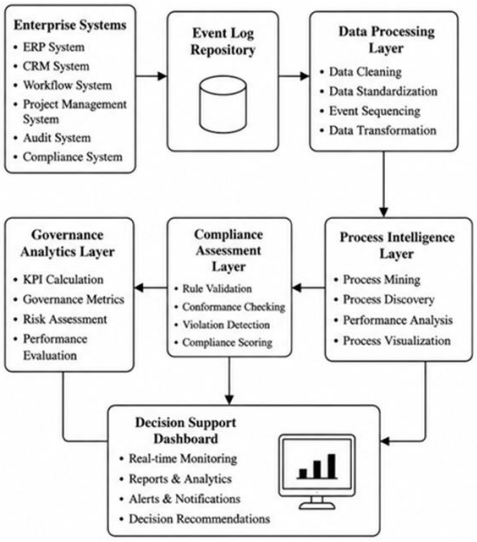


Fig.3 System Architecture of the Proposed Framework.

C. Data Collection and Preprocessing

The proposed framework is designed to integrate event data from enterprise resource planning systems, customer relationship management systems, workflow management systems, project management information systems, audit information systems, compliance management systems, human resource management systems, and business intelligence platforms. These systems represent potential data sources for the framework. The event data are organized into a standardized structure containing Case ID, Activity Name, Timestamp,

Resource ID, Project ID, and Process Status. Data preprocessing includes duplicate removal, missing value treatment, timestamp standardization, activity coding, attribute normalization, and event sequence validation.

Table I. *Data Sources and Characteristics Used in the Proposed Framework.*

Data Source	Data Type	Main Attributes	Purpose in the Framework
Enterprise Resource Planning (ERP)	Transaction logs	Transaction ID, Timestamp, Department, Status	Analyze operational workflows and resource utilization
Workflow Management System	Event logs	Case ID, Activity, Timestamp, Performer	Process mining and workflow reconstruction
Project Management Information System (PMIS)	Project records	Project ID, Task ID, Milestone, Completion Status	Project progress monitoring and governance evaluation
Customer Relationship Management (CRM)	Service records	Customer ID, Request Type, Resolution Time	Evaluate service delivery performance
Compliance Management System	Compliance records	Rule ID, Compliance Status, Violation Type	Compliance assessment and violation detection
Audit Information System	Audit logs	Audit ID, Finding, Risk Level	Governance verification and internal control assessment
Human Resource Management System (HRMS)	Resource records	Employee ID, Role, Workload	Resource utilization analysis
Business Intelligence Platform	KPI reports	KPI Name, Value, Target	Governance performance evaluation

Table II. *Data Cleaning and Preprocessing Procedures.*

Data Quality Issue	Detection Method	Processing Technique	Expected Outcome
Missing values	Null value detection	Mean, mode, or interpolation	Complete dataset
Duplicate records	Duplicate key matching	Duplicate removal	Unique process instances
Timestamp inconsistency	Time validation	Standardization (ISO 8601)	Chronological consistency
Invalid activity names	Dictionary matching	Activity coding	Standardized activity labels
Outlier execution time	Interquartile Range (IQR)	Outlier filtering	Stable analytical results
Incorrect resource	Reference lookup	Identifier correction	Accurate resource

identifiers			mapping
Incomplete event sequences	Sequence validation	Case reconstruction	Complete event logs

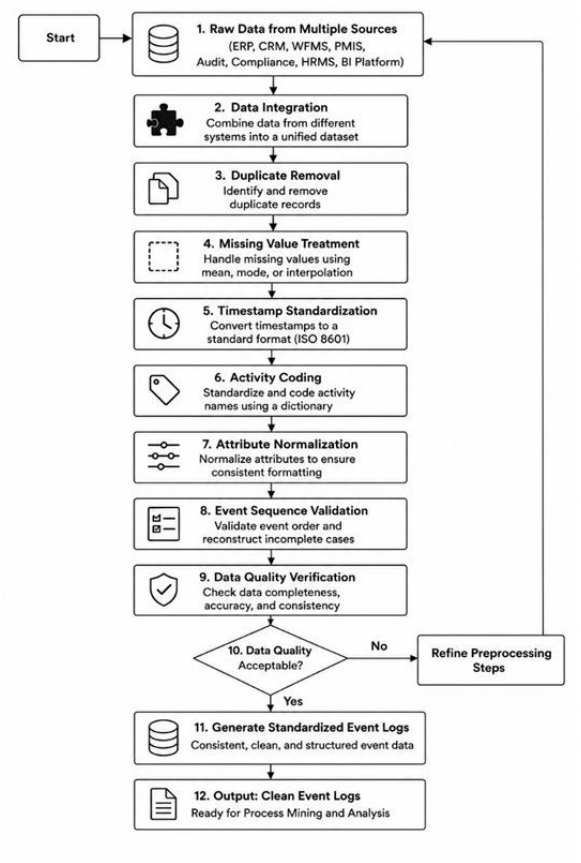


Fig.4 Data Preprocessing Workflow

D. Process Intelligence and Analytical Model

The analytical model applies process mining techniques to reconstruct business processes, evaluate process performance, identify compliance deviations, and calculate governance indicators. Quantitative performance metrics are computed using the following equations.

The business process model was reconstructed from the standardized event log using process mining techniques. The discovered model represents the observed sequence of activities, transitions, and workflow deviations within the evaluated process instances.

The Cycle Time is calculated as,

$$CT = \frac{\sum_{i=1}^{n} \left(T_{end,i} - T_{start,i}\right)}{n}$$

Where, T_{start} and T_{end} denote the starting and ending times of each process instance. This metric represents the average execution time of completed cases.

The Compliance Rate is calculated as,

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

Where, N_C represents compliant process instances and N_t represents the total number of process instances. This equation measures the proportion of process executions that satisfy organizational compliance requirements.

The Resource Utilization is calculated as

$$RU = \frac{T_{active}}{T_{available}} \times 100$$

Where, T_{active} denotes productive working time and $T_{available}$ denotes total available working time.

The Governance Performance Index (GPI) is calculated as

$$GPI = \sum_{i=1}^{m} W_i S_i$$

Where, S_i is the normalized score of governance indicator$i$, and W_i is its corresponding weight. The GPI summarizes governance performance into a single evaluation score.

Table III. *Governance Performance Indicators*

Indicator	Symbol	Unit	Description
Cycle Time	CT	Hours	Average elapsed time from case initiation to case completion across completed process instances.
Throughput Time	TT	Hours	Elapsed time between the start and completion of an individual process instance.
Compliance Rate	CR	%	Percentage of compliant process instances
Resource Utilization	RU	%	Percentage of productive resource usage
Activity Frequency	AF	Count	$AF_a = N_a$, where N_a is the number of occurrences of

			activity a
Process Deviation Rate	*PDR*	%	$PDR = \frac{NT}{ND} \times 100$, where N_D is the number of process instances with at least one deviation and N_T is the total evaluated process instances
Governance Performance Index	*GPI*	Score	$GPI = \sum_{i=1}^{n} W_i S_i$, where S_i is the normalized score of governance indicator i, and W_i is its corresponding weight, with $\sum_{i=1}^{n}$ 1
Process Efficiency	*PE*	%	$PE = \frac{TE}{TP} \times 100$, where T_p is productive execution time and T_E is total elapsed execution time

Table IV. *Compliance Assessment Rules.*

Rule ID	Compliance Rule	Evaluation Criterion
R1	Activity sequence follows approved workflow	Process model conformance
R2	Mandatory approval completed	Approval log verification
R3	Project completed within planned duration	Cycle time threshold
R4	Resource assigned according to policy	Resource allocation rules
R5	No unauthorized process execution	Authorization validation
R6	Required documents uploaded	Document verification
R7	Audit trail completeness	Event log completeness
R8	KPI threshold satisfied	KPI comparison

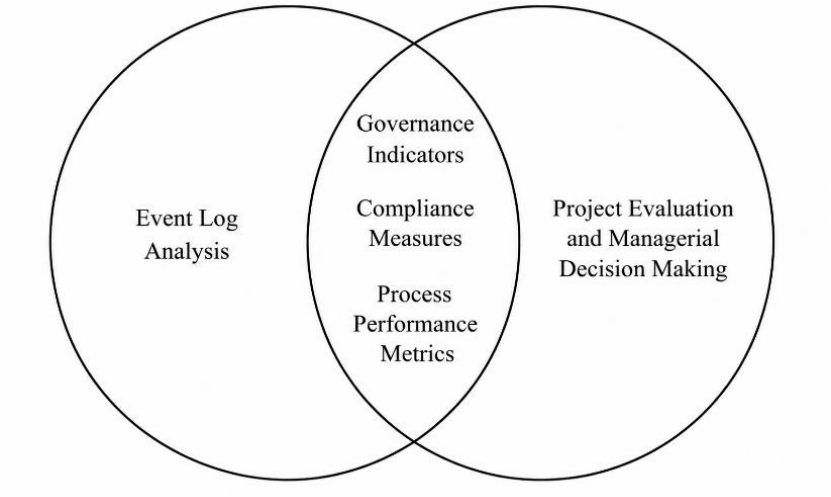


Fig.5 Process Intelligence Analytical Model.

Figure 5 illustrates the analytical relationship among event log analysis, compliance assessment, process performance measurement, and project governance evaluation.

E. Validation

The proposed framework is evaluated using classification metrics and governance consistency analysis. Accuracy, Precision, Recall, and F1 Score are calculated from the confusion matrix to assess compliance classification performance. For classification-based compliance evaluation, non-compliant process instances are treated as the positive class. Precision represents the proportion of predicted non-compliant cases that are actually non-compliant, while Recall represents the proportion of actual non-compliant cases correctly identified by the model. Governance indicators are evaluated separately using the defined process, compliance, and resource related measures. Model performance is assessed using Accuracy, Precision, Recall, and F1 Score.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Prrecision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

Where, TP**,** TN**,** FP and FN represent true positives, true negatives, false positives, and false negatives, respectively. These metrics evaluate the reliability of compliance detection and governance assessment.

Table V. *Performance Evaluation Metrics*

Metric	**Formula**	**Interpretation**
Accuracy	(TP + TN)/(TP + TN + FP + FN)	Overall classification performance
Precision	TP/(TP + FP)	Correctness of compliance detection
Recall	TP/(TP + FN)	Ability to identify non-compliant

		cases
F1 Score	$F1 = \frac{2 \times Precision \times R}{Precision + Rec}$	Balance between precision and recall
Governance Score Consistency	Standard Deviation of GPI	$SD_{GPI} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n} (GPI - \underline{GPI})^2}$

IV. Results and Discussion

The proposed framework was evaluated using a simulated standardized event-log dataset structured according to the process, activity, resource, and compliance attributes defined in the methodology . The analysis included process mining, compliance assessment, governance evaluation, resource utilization analysis, and classification-based validation. The results are presented in terms of process characteristics, compliance outcomes, governance indicators, and validation performance.

A. Results

Data preprocessing produced a standardized event log dataset after duplicate removal, timestamp standardization, activity coding, and event sequence validation. The processed dataset was used for process mining and governance analysis.

Table VI. *Summary Statistics of the Process Event Log Dataset.*

Attribute	**Value**
Total Process Instances	5,240
Total Event Records	68,415
Recorded Activities	34
Organizational Resources	118
Projects Analyzed	72
Compliance Rules	8
Average Events per Case	13.1
Average Cycle Time	21.8 hours

The process mining analysis reconstructed the business workflow and identified several deviations from the reference process model. Most deviations occurred during approval activities and task reassignment, indicating areas requiring governance review.

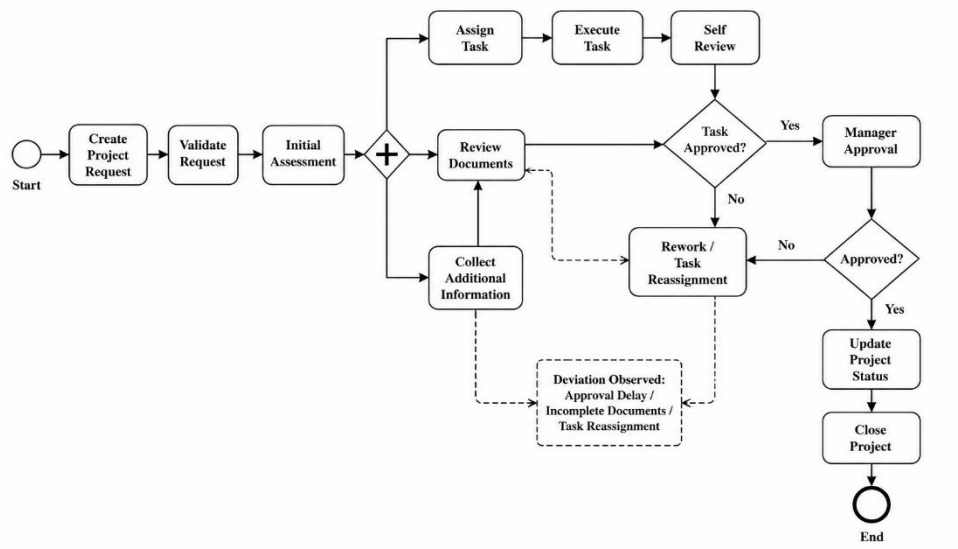


Fig.6 Discovered Business Process Model.

Compliance assessment showed that most process instances satisfied organizational policies, while a smaller proportion contained violations related to missing approvals, delayed execution, and incomplete documentation.

For reporting purposes, each non compliant process instance was assigned to one primary violation category. Therefore, the counts for missing approval, delayed activities, and documentation issues sum to the total number of non-compliant cases.

Table VII. *Compliance Assessment Results.*

Compliance Indicator	**Value**
Compliant Cases	4,681 (89.3%)
Non-Compliant Cases	559 (10.7%)
Missing Approval	186
Delayed Activities	214
Documentation Issues	159
Overall Compliance Rate	89.3%

Governance evaluation showed variation in Governance Performance Index (GPI) scores across process instances with different compliance outcomes. The analysis also showed differences in execution time across the evaluated process instances .

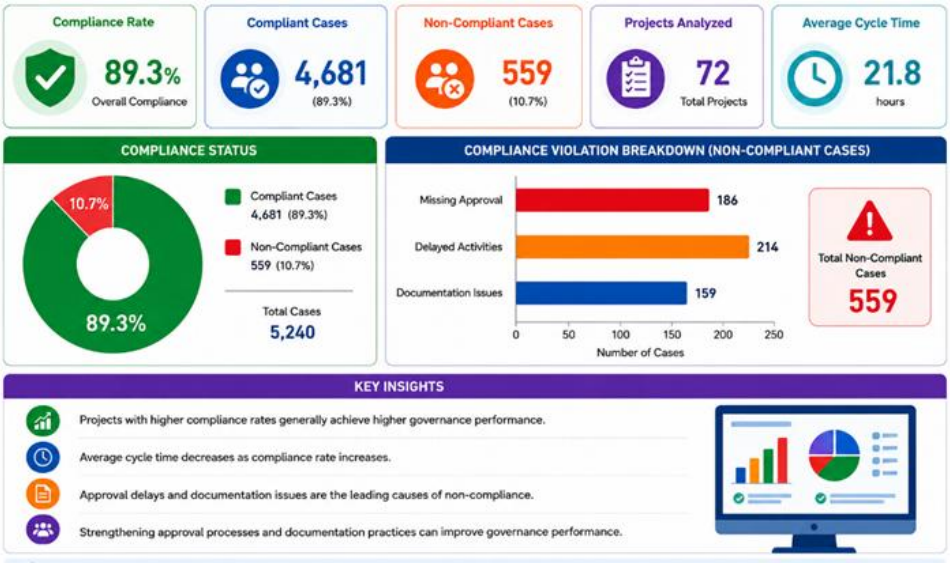


Fig.7 Governance Performance Dashboard.

Figure 7 presents the governance performance dashboard, summarizing compliance status, project coverage, non-compliant cases, violation categories, and average cycle time across the evaluated process instances. The dashboard provides an integrated view of compliance and process performance for governance monitoring.

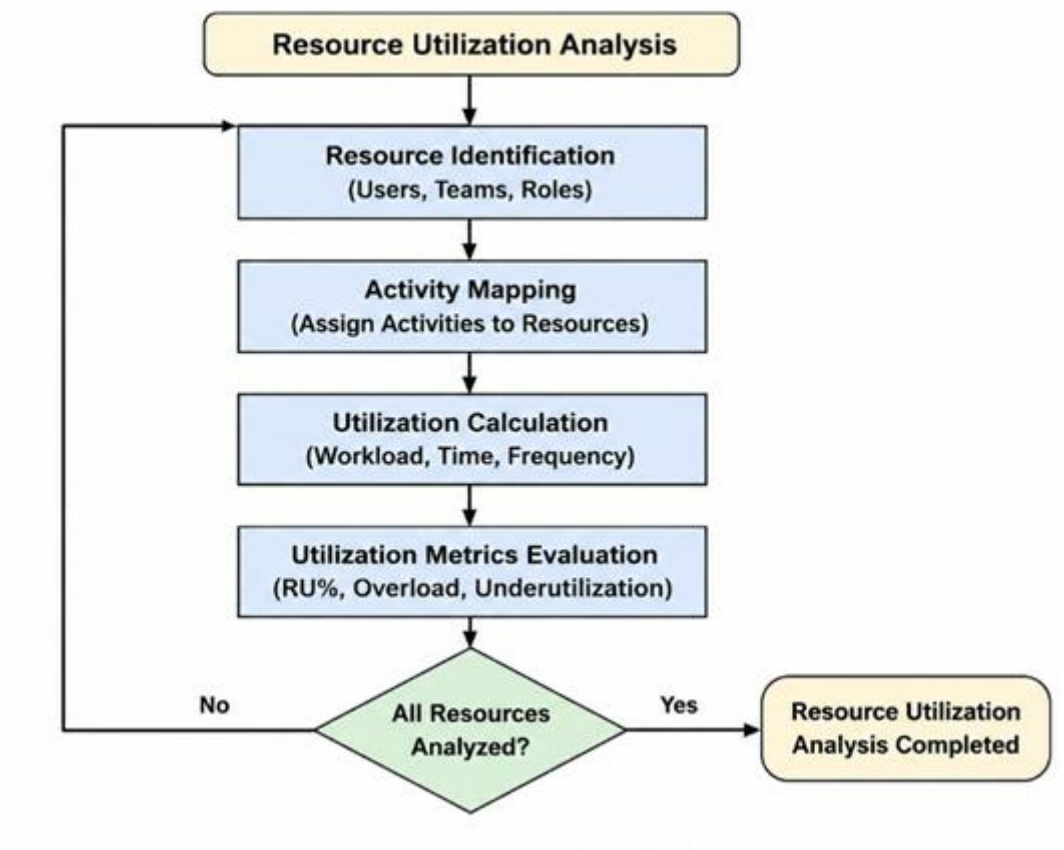


Fig.8 Resource Utilization Analysis.

Figure 8 presents the resource utilization analysis across the evaluated resources in the simulated dataset. The analysis examines resource workload, activity assignments, utilization levels, and workload distribution across the evaluated resources.

Table VIII. *Validation Results.*

Performance Metric	Value
Accuracy	95.4%
Precision	93.8%
Recall	92.6%
F1 Score	93.2%

B. Discussion

The results show that process intelligence supports project governance through systematic analysis of enterprise event logs. Process mining identified workflow deviations that were not visible in conventional project reports. Compliance assessment and governance analytics provided a unified view of project execution, organizational compliance, and operational performance. The Governance Performance Index combined multiple governance indicators into a single score, allowing consistent comparison among projects. Resource utilization analysis also identified workload imbalance, indicating opportunities for improving project coordination and resource allocation

C. Limitations and Future Work

The proposed framework was evaluated using standardized enterprise event log data and predefined governance rules. Different organizations may require different compliance policies and governance indicators. Future studies should evaluate the framework using larger datasets collected from multiple industries and incorporate real-time event stream processing, explainable AI, predictive governance analytics, and advanced process mining algorithms to support continuous project governance.

V. Conclusion

This study proposed a Process Intelligence Framework for Compliance-Aware Project Governance in Digital Service Organizations that integrates process mining, event log analytics, compliance assessment, governance analytics, and AI-supported decision support. The objective was to provide a systematic approach for monitoring business processes, evaluating compliance, and supporting project governance through enterprise event log analysis. The results indicate that the proposed framework identifies process deviations,

measures governance performance, evaluates compliance, and supports project monitoring using quantitative performance indicators. The integrated analytical approach provides a unified view of process execution and governance performance, making it suitable for project evaluation in digital service organizations. The proposed framework can support project managers and compliance teams through continuous governance monitoring and performance assessment. Future research should evaluate the framework using larger datasets from multiple organizations and investigate real-time process monitoring, explainable AI, predictive governance analytics, and advanced process mining methods to extend its application across different digital service environments.

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