Preference-Aware Process Analytics for Enterprise Operations: Event-Log Mining, Multi-Criteria Model Selection, and Business Performance Interpretation

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Abstract

Enterprise process analytics has moved from descriptive dashboarding toward decision-oriented interpretation of event logs. However, process discovery still often depends on default algorithm settings, informal preprocessing decisions, and technical quality scores that are difficult for managers to translate into business action. This article develops a preference-aware process analytics framework for enterprise operations. The framework combines event-log mining, candidate discovery pipelines, multi-criteria model selection, and business performance interpretation in a single analytical workflow. Instead of treating fitness, precision, simplicity, generalization, stability, and computational cost as isolated technical indicators, the proposed approach converts them into weighted preference profiles that reflect operational priorities such as compliance, lead-time reduction, service reliability, cost-to-serve control, and managerial interpretability. A numerical study using three calibrated enterprise event-log settings - order-to-cash, procure-to-pay, and service-desk resolution - demonstrates how different preference structures change the recommended process model and alter subsequent business conclusions. The results show that balanced preference-aware selection improves composite interpretation scores by 13.8% relative to default discovery, reduces analyst review time by 25.6% to 33.1% across the three settings, and improves the consistency between discovered process variants and business key performance indicators. Sensitivity analysis further indicates that precision-oriented preferences protect compliance interpretation but may reduce simplicity and managerial readability, while efficiency-oriented preferences improve runtime but may hide low-frequency exceptions. The study contributes to business data analytics by reframing process discovery as a managerial decision problem rather than a purely technical modeling problem. It also offers practical guidance for organizations seeking to govern process mining projects, document selection assumptions, and connect event-log evidence to performance improvement decisions.

Keywords: Process analytics; Event-log mining; Business data analytics; Multi-criteria decision-making; Process discovery; enterprise operations; preference-aware model selection; business performance interpretation

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1. Introduction

Enterprise operations now generate detailed digital traces through enterprise resource planning systems, customer relationship management platforms, warehouse management systems, service-desk applications, workflow engines, robotic process automation tools, and cloud collaboration environments. These digital traces are often recorded as event logs in which each case, activity, timestamp, resource, status transition, and business object leaves a traceable record. For business data analytics, such logs are more than technical audit trails. They contain evidence about how work actually moves across organizational units, which variants absorb managerial attention, where delays accumulate, which exceptions become routine, and how local decisions shape enterprise-level performance. Process mining has therefore become an important analytical bridge between information systems data and operational management, enabling organizations to discover, monitor, and improve business processes from event data rather than relying solely on interviews or static process documentation. This framing follows the process mining view that event records can connect operational execution with improvement evidence (van der Aalst et al., 2012). It is also consistent with the broader argument that artificial intelligence extends managerial analytics when data traces are converted into decision evidence (Lu, 2019).

Despite this promise, process discovery remains difficult to use as a managerial decision tool. A process analyst rarely faces a single obvious model. The same event log can produce different process maps depending on event-log cleaning rules, trace filtering thresholds, discovery algorithms, conformance settings, and hyperparameter choices. One model may fit most observed behavior but include a large number of low-value branches. Another may be compact and easy to explain but omit infrequent compliance exceptions. A third may reveal more deviations but require a longer runtime and deeper technical interpretation. These trade-offs mean that the best process model is not always the model with the highest technical fitness. It is the model that best supports the decision context in which the model will be used. Event-log quality research shows that missing, inconsistent, or ambiguous log attributes can materially change the managerial meaning of a discovered process (Suriadi et al., 2017).

The software research direction motivating this article concerns automated process discovery configuration. It highlights three issues that are directly relevant for business analytics: process model quality is highly sensitive to preprocessing and algorithmic settings; the search space of candidate configurations is too large for exhaustive manual exploration; and multiple quality metrics may conflict, requiring a multi-objective formulation. It also emphasizes a weight-based model selection mechanism and parallel evaluation of candidate configurations. These ideas are valuable, but their managerial implications require a separate business analytics treatment. A business journal article should not merely ask whether an optimization pipeline can identify a technically strong process model. It should ask how managers express preferences, how those preferences change model selection, and how selected models are interpreted as evidence for enterprise performance improvement. Recent discussions of process science similarly emphasize that process models should be evaluated for their contribution to organizational understanding, not only for their technical elegance (Reijers, 2021).

This study develops business analytics treatment. The proposed framework reframes event-log mining as a preference-aware decision process. The central argument is simple: process discovery creates a portfolio of plausible operational representations, and model selection should explicitly incorporate stakeholder priorities. A compliance officer may prefer precision and exception visibility; a service operations manager may prefer speed, stability, and cycle-time interpretability; a cost analyst may prefer a model that supports cost-to-serve allocation; a digital transformation team may prefer a model that balances simplicity and

completeness for communication. When these preferences remain implicit, organizations risk choosing models because they are technically convenient or visually appealing. When preferences are made explicit, selection becomes auditable, repeatable, and aligned with the business purpose of the analysis. A design stance grounded in business data analytics therefore requires the model selection task to remain connected to managerial purpose and traceable evidence (vom Brocke et al., 2021).

The article addresses three research questions. First, how can event-log mining be organized so that discovery pipelines produce a structured portfolio of candidate models rather than a single default representation? Second, how can multi-criteria model selection incorporate business preferences without reducing process discovery to arbitrary weighting? Third, how can the selected model be translated into interpretable performance conclusions about cycle time, compliance, service reliability, and operational cost? The study answers these questions by presenting a preference-aware framework, developing a compact scoring procedure, and conducting a numerical study across three enterprise operations.

The contributions are fourfold. First, the article connects process discovery with business data analytics by treating model selection as a managerial decision under competing quality criteria. Second, it proposes a preference-aware scoring procedure that links technical metrics to business goals while preserving transparency about the role of stakeholder priorities. Third, it provides a data analysis design for comparing candidate models across order-to-cash, procure-to-pay, and service-desk processes. Fourth, it offers managerial implications for process mining governance, including how organizations can document selection assumptions, balance interpretability with accuracy, and avoid misleading performance narratives. The remainder of the article is organized as follows. Section 2 reviews the relevant literature. Section 3 introduces the framework and scoring logic. Section 4 describes the data and experimental design. Section 5 presents results. Section 6 discusses managerial implications. Section 7 identifies limitations and future research directions. Section 8 concludes the study.

2. Literature Review

2.1 Process Mining and Enterprise Operations Analytics

Process mining emerged as a data-driven approach for connecting event logs to process understanding. Early work on process mining emphasized the discovery of process models, the checking of conformance between observed and prescribed behavior, and the extension of process models with performance information. In enterprise contexts, this perspective is particularly important because operational performance is often embedded in hidden sequences of handoffs, rework, approvals, and exception handling. A process that appears efficient in a formal procedure may reveal substantial delays when its event log is analyzed at the case level. Conformance-oriented research further demonstrates that event logs can reveal deviations between executed work and prescribed procedures (Rozinat and van der Aalst, 2008). Business process management literature has long recognized the need to align process models with organizational goals, customer value, and control requirements. However, classical process documentation and improvement methods tend to rely heavily on interviews, workshops, and manually maintained process diagrams. Event-log mining changes the evidence base by allowing analysts to reconstruct actual execution paths. This makes it possible to compare formal procedures with lived operational behavior, detect bottlenecks that are invisible in process manuals, and evaluate whether standard operating procedures are consistently followed across departments or branches. Research on business process improvement shows that organizational size, culture, and resources influence improvement activities (Beerepoot et al., 2019). The broader business process management literature supports this view by treating process models as coordination devices for analysis, redesign, and governance (Dumas et al., 2013).

For business data analytics, the analytical value of process mining lies not only in visualization but also in decision support. Event logs can support cycle-time analysis, compliance analysis, resource allocation, service level monitoring, root-cause diagnosis, and automation prioritization. Yet these applications require a careful translation from low-level event data to high-level business indicators. A process map with excellent technical fit maybe too complex for a managerial meeting. Conversely, a simplified process map may support communication but hide the exception cases that generate cost or regulatory risk. Therefore, process analytics requires a selection logic that is both technically defensible and business aware. This decision-support orientation is aligned with prescriptive analytics research, which treats operational data as a basis for recommending actions rather than merely explaining the past (Bertsimas and Kallus, 2020).

2.2 Process Discovery, Model Quality, and Event-Log Preparation

Process discovery algorithms seek to construct process models from event logs. Well-known approaches include heuristic mining, fuzzy mining, inductive mining, split mining, and evolutionary approaches. These algorithms differ in their assumptions about noise, concurrency, loops, infrequent behavior, and model structure. They also differ in the type of model they produce and in the ease with which managers can interpret the resulting representation. Because business event logs often contain duplicate labels, missing timestamps, exceptional traces, manual workarounds, and changes in policy over time, discovery results are highly sensitive to preprocessing decisions. Research on process-mining workflows highlights the need to evaluate alternative techniques and parameter settings (Bolt et al., 2016). Automated extraction of event logs from enterprise databases also shows that discovery quality depends on the upstream data model, not only on the mining algorithm (Andrews et al., 2020). Inductive mining research provides a representative example of how structural guarantees in discovery algorithms can improve the clarity of event-log-derived models (Leemans et al., 2013).

The most widely discussed quality dimensions are fitness, precision, generalization, and simplicity. Fitness measures how well the discovered model can replay observed traces. Precision measures whether the model avoids allowing too much behavior that did not occur. Generalization addresses whether the model captures likely but unobserved behavior rather than merely memorizing the log. Simplicity reflects the idea that, all else equal, a clearer model is easier to understand and maintain. These dimensions create inherent trade-offs. A very permissive model may have high fitness but poor precision. A highly precise model may become too complex for business use. A simple model may communicate well but fail to represent important variations. Declarative monitoring research reinforces the importance of separating observed behavior from allowed behavior when analysts interpret compliance-related variants (Mannhardt et al., 2016). Alignment-based conformance checking provides a rigorous way to compare event traces with

modeled behavior under deviations and missing events (de Leoni and van der Aalst, 2013). The four standard discovery quality dimensions are often formalized through fitness, precision, generalization, and simplicity (Buijs et al., 2012).

Event-log preparation is equally important. Filtering rare traces can remove noise but may also remove meaningful exceptions. Timestamp repair can improve cycle-time analysis but may introduce assumptions about missing data. Resource aggregation can protect privacy but may hide workload imbalances. Case attribute selection can improve model relevance but may bias interpretation toward easily measured aspects of performance. These issues suggest that model quality should not be judged only by algorithm output. It should be judged by a pipeline that includes data preparation, algorithm selection, metric computation, and business interpretation. A study of process-map design documents the diversity of modeling concepts used in practice (Malinova et al., 2015). Privacy-aware process mining further shows that preprocessing decisions may protect sensitive traces while also changing the analytical properties of the log (Fahrenkrog-Petersen et al., 2023).

2.3 Multi-Criteria Decision-Making and Preference-Aware Analytics

Multi-criteria decision-making provides a useful conceptual foundation for preference-aware process analytics. In many decision problems, alternatives must be evaluated across criteria that cannot be reduced to a single natural unit. Classical decision analysis therefore uses weights, value functions, outranking methods, and sensitivity analysis to make trade-offs explicit. In process discovery, the alternatives are candidate models or candidate discovery pipelines, while the criteria include technical quality, runtime, stability, interpretability, and business KPI alignment. The analytic hierarchy process offers one widely used way to translate qualitative judgments into structured priority weights (Saaty, 2008). Multi-criteria decision-making surveys confirm that weighted scoring, ranking, and compromise methods remain valuable when decision criteria are heterogeneous (Mardani et al., 2015).

Preference-aware analytics differs from simple weighted scoring when it requires stakeholders to state why a criterion matters, how weights are selected, and how robust the selection is to plausible changes in those weights. This distinction is important for enterprise governance. A procurement compliance team might weight precision more heavily because false allowance of noncompliant paths is risky. A customer service team might weight cycle-time interpretability more heavily because managers need to identify delays quickly. A finance operations team might weight cost attribution more heavily because the model must support process costing. By documenting these choices, the organization can explain why different business functions may legitimately select different process models from the same event log. The multiple-criteria decision analysis literature also shows that decision quality depends on explaining preference structures rather than only calculating a final score (Greco et al., 2016). Outranking theory is useful here because it recognizes that alternatives may dominate each other only under certain preference assumptions (Roy, 1991).

Multi-objective optimization literature also emphasizes that no single solution is best across all objectives when trade-offs exist. The managerial challenge is therefore not to hide the trade-off but to make it visible. In process analytics setting, the Pareto frontier can be understood as a set of non-dominated candidate models. The final choice should reflect business preferences rather than merely a technical default. This study builds on this logic but keeps the scoring procedure deliberately transparent so that it can be used in business analytics projects without requiring extensive mathematical expertise. Evolutionary multi-objective optimization research provides a basis for treating candidate process models as a frontier of trade-offs rather than as one universally optimal output (Deb et al., 2002). Contemporary surveys of multi-objective optimization similarly emphasize that solution selection requires a decision-maker's preference model after the search process (Emmerich and Deutz, 2018). Runtime verification can translate process evidence into operational alerts and control signals (Maggi et al., 2012).

A selected process model may support interpretation in several ways. It may group variants into understandable families, reveal rework loops, identify activities that precede delays, expose compliance detours, or show where resources are repeatedly involved in exception handling. Yet the business meaning of these findings depends on the selected model. If a model hides infrequent variants, the analyst may underestimate compliance risk. If a model displays every rare trace, the analyst may overstate complexity and fail to focus on dominant operational problems. This is why preference-aware selection matters: the model determines the performance story that managers will hear. Predictive monitoring studies show that event-log features can support forecasts of remaining time, outcomes, and risk exposure during process execution (Tax et al., 2017). Predictive business process monitoring has also been extended to multi-perspective settings in which activities, resources, and case attributes jointly shape interpretation (Di Francescomarino et al., 2018).

The literature still contains a gap between technical process mining metrics and business analytics interpretation. Many studies evaluate models using process mining quality measures, while many

management studies discuss process improvement without specifying how technical model selection influenced the conclusions. This article addresses that gap by explicitly linking candidate model selection to business performance interpretation. The goal is not to replace technical evaluation. The goal is to embed technical evaluation in a transparent decision framework that respects business priorities. Data-quality work on event logs confirms that the reliability of downstream discovery depends on how accurately cases, timestamps, activities, and resources are recorded (Dakic et al., 2023). Object-centric process mining expands this point by showing that modern enterprises often need to analyze multiple interacting business objects rather than a single case notion (van der Aalst, 2023)

3. Research Framework and Method

3.1 Enterprise Event-Log Setting

The proposed framework assumes that an organization has access to event logs from operational systems. Each event record contains at least a case identifier, an activity label, and a timestamp. Additional attributes may include resource, department, location, customer segment, product family, priority level, value amount, and compliance status. The framework is designed for enterprise operations in which managers need to understand actual process behavior rather than merely produce a visually attractive map. Typical applications include order-to-cash, procure-to-pay, claims handling, customer onboarding, service-desk resolution, and internal approval workflows. Emerging work on large language models for event-log extraction suggests that automated preprocessing may increasingly shape the quality of process analytics pipelines (Stein Dani et al., 2025). Blockchain technology research also indicates that future enterprise workflows will generate richer and more decentralized trace data requiring stronger verification and governance (Zheng and Lu, 2022).

The analytical unit is a candidate discovery pipeline. A pipeline consists of four components: a log preparation rule, a process discovery algorithm, a hyperparameter configuration, and a model evaluation procedure. For example, one pipeline may apply a trace frequency filter, use inductive mining, select a noise threshold of 0.20, and evaluate the resulting model using alignment-based fitness and precision. Another pipeline may keep rare traces, use a heuristic miner, and evaluate simplicity and runtime more heavily. Treating the pipeline rather than the algorithm as the unit of analysis is important because preprocessing and parameter choices are often as influential as the choice of discovery algorithm itself. Automated machine learning research provides a useful analogy because it treats configuration selection as a systematic search over model and hyperparameter choices (Feurer and Hutter, 2019). Sequential model-based optimization similarly supports efficient exploration of expensive configuration spaces when exhaustive search is infeasible (Hutter et al., 2011).

The output of the discovery stage is not a single model, but a candidate set. This candidate set represents alternative views of the same operational evidence. Some candidates are technically accurate but complex. Some are stable and simple but less precise. Some reveal exception paths that matter for audit and compliance. Others summarize the mainstream process and are easier for managers to use during improvement workshops. The preference-aware stage then converts this candidate set into a business-aligned recommendation. Auto-WEKA shows that joint algorithm selection and hyperparameter optimization can outperform manual configuration in complex analytical tasks (Thornton et al., 2013). Automated algorithm configuration research further shows that tunable parameter spaces can be explored in a reproducible way when search procedures are explicitly specified (Lopez-Ibanez et al., 2016). Table 1 summarizes the core components of the proposed framework.

Table 1. Core Components of the Preference-Aware Process Analytics Framework

Component	Role in the framework	Business interpretation question
Event-log evidence	Captures cases, activities, timestamps, resources, and attributes	What actually happened in enterprise operations?
Discovery portfolio	Generates alternative process models under different pipelines	Which representations ofthe same process are technically plausible?
Quality metrics	Measures fitness, precision, generalization, simplicity, stability, and runtime	What is gained or lost by selecting each model?
Preference profile	Assigns weights and thresholds based on stakeholder priorities	Which trade-offs are acceptable for this business purpose?
Performance interpretation	Links the selected model to cycle time, compliance, cost, and service reliability	What managerial decision follows from the model?

3.2 Preference-Aware Scoring Logic

The framework evaluates each candidate model against a set of standardized criteria. Let each candidate model be indexed by j and each evaluation criterion be indexed by k. Criteria may include process mining quality measures, computational indicators, and business interpretation measures. Because criteria use different scales, each criterion is transformed into a normalized score. For beneficial criteria such as fitness and interpretability, higher values are better. For cost criteria such as runtime or excessive model complexity, the scale is reversed so that a higher normalized score still represents a more desirable outcome. Recent work on trustworthy process mining underlines the need to justify automated recommendations when process evidence affects organizational decisions (Mannhardt, 2022). Compromise-ranking research also shows that decision support systems should expose trade-offs, weights, and ranking sensitivity when alternatives are close (Opricovic and Tzeng, 2004).

The composite preference score is then calculated as a weighted sum of normalized criterion values. The weights represent stakeholder priorities rather than mathematical truth. They should be elicited through interviews, workshops, or governance rules and should be documented before the final model is selected. The scoring rule used in this study is intentionally simple: each candidate receives a weighted average of normalized criteria so that managers can understand how the recommendation is produced. Responsible use of process mining also requires awareness of employee privacy, surveillance risk, and data protection obligations (Ileri et al., 2025). Research on organizational process-mining setups shows that governance mechanisms should accompany technical deployment (Marcus et al., 2026). Scoring rule: Candidate score = weighted average of normalized technical and business interpretation criteria.

In this scoring rule, the candidate score represents the overall suitability of a model, the criterion weights represent stakeholder priorities, and the normalized criterion values represent comparable evidence across technical and business dimensions. The selected model is the candidate with the highest composite score subject to minimum thresholds on essential criteria. For example, an organization may require fitness above 0.80 and precision above 0.70 before business interpretation is allowed. Thresholds prevent a model from being selected merely because it performs well on less critical criteria.

The framework also supports sensitivity analysis. Instead of reporting only one selected model, the analyst evaluates how the recommendation changes as the weight profile changes. If the same model remains preferred across plausible weights, the recommendation is robust. If the selected model changes quickly

when one weight is adjusted, the organization should interpret the result more cautiously and discuss the underlying trade-off. Sensitivity analysis is especially important when different departments disagree on whether the model should prioritize compliance, efficiency, or simplicity. Information-security risk assessment can be linked to business processes and the flow of security data (Shameli-Sendi, 2020). Modern hyperparameter optimization platforms also demonstrate the value of transparent experimental records for comparing candidate analytical configurations (Akiba et al., 2019).

3.3 Business Performance Mapping

After the model is selected, the framework maps process model features to business performance indicators. This step is not automatic in a purely statistical sense; it combines event-log measurements with managerial definitions of operational performance. For example, a rework loop in an order-to-cash process may be mapped to invoice correction cost. A repeated approval detour in a procure-to-pay process may be mapped to compliance and procurement lead time. A reassignment loop in a service-desk process may be mapped to service level agreement risk. The selected model provides the structural lens through which these indicators are interpreted. Deep learning studies of predictive process monitoring illustrate how event-log features may be transformed into business-relevant predictions (Neu et al., 2022). Hierarchical attention models further show that both trace-level and activity-level signals can contribute to interpretable process predictions (Jalayer et al., 2022).

To maintain transparency, the framework uses a business interpretation index that aggregates four managerial dimensions: cycle-time explanation, cost-to-serve relevance, compliance visibility, and service reliability. The index is not a replacement for detailed operational analysis. It is a summary measure that helps compare how well different process models support business interpretation. The interpretation index used in the numerical study gives balanced attention to cycle-time explanation, cost-to-serve relevance, compliance visibility, and service reliability. Explainable artificial intelligence research stresses that users need understandable reasons for model outputs in decision contexts (Barredo Arrieta et al., 2020). Surveys of interpretable machine learning similarly show that explanations should be adapted to the decision-maker and the task (Guidotti et al., 2018).

In this index, the four dimensions represent the main managerial questions that process analytics usually needs to answer: where time is lost, where cost is created, where compliance risk appears, and where service reliability is weakened. The weights reflect a balanced enterprise operations setting. In a regulated financial process, the compliance visibility weight may be higher. In a customer support process, the service reliability weight may be higher. The purpose is to make these choices explicit rather than bury them in informal interpretation.

The final analytical report produced by the framework contains five elements: a description of the event log, the candidate discovery portfolio, the preference profile, the selected model, and the business performance interpretation. This structure supports governance because another analyst can reproduce the selection logic, inspect the rejected alternatives, and understand why the chosen model is appropriate for the stated business question. This requirement is consistent with the argument that interpretability should be evaluated in relation to the decision problem, not as a purely technical property (Lipton, 2018).

4. Experimental Design and Data

4.1 Event-Log Scenarios

To evaluate the framework, this study constructs three calibrated event-log scenarios that represent common enterprise operations. The first scenario is an order-to-cash process covering sales order confirmation, credit check, picking, shipment, invoicing, payment matching, and exception resolution. The

second is a procure-to-pay process covering purchase request, approval, supplier confirmation, goods receipt, invoice verification, and payment. The third is a service-desk resolution process covering ticket intake, classification, assignment, investigation, escalation, customer confirmation, and closure. These scenarios are not intended to reproduce a specific company. They are designed to approximate realistic operational patterns that are frequently encountered in business process analytics projects. Process mining applications in healthcare show that event-log analysis can reveal pathway variation and operational constraints in service environments (De Roock and Martin, 2022). Process mining has also been used to improve workflows for preparing and delivering data (Abrehdari, 2025).

Each scenario includes mainstream traces, infrequent exceptions, timestamp variability, rework loops, and resource handoff patterns. Noise was calibrated to represent typical enterprise data quality problems, including duplicate events, late updates, inconsistent activity labels, and cases with missing close events. The event-log statistics are presented in Table 2. The logs are large enough to create meaningful discovery trade-offs but small enough to support transparent interpretation. Recent research on shaping event data for process mining suggests that traceability and preprocessing assumptions should be built into the analytical design from the beginning (Pradhan et al., 2025). Research on event-log data quality proposes simulation of data-quality issues to evaluate preprocessing solutions (Comuzzi et al., 2025).

Table 2. Event-Log Scenarios Used in the Numerical Study

Log scenario	Cases	Events	Activities	Median duration	Exception share
Order-to-cash	2,412	18,036	17	6.8 days	11.4%
Procure-to-pay	1,780	13,415	19	9.3 days	14.7%
Service-desk resolution	4, 105	25,690	15	18.6 hours	18.9%

4.2 Candidate Discovery Pipelines

For each event-log scenario, candidate models were generated using combinations of preprocessing rules, discovery algorithms, and hyperparameter settings. The preprocessing rules included no filtering, infrequent trace filtering, timestamp repair, activity label aggregation, and case duration trimming. The discovery algorithms included heuristic mining, inductive mining, split mining, and evolutionary tree mining. Hyperparameters controlled noise thresholds, filtering levels, and model simplification settings. The candidate set for each log was intentionally diverse so that the selection problem would contain meaningful trade-offs. Explainable recurrent models for business process prediction show that candidate evaluation should include both predictive accuracy and human interpretability (Hanga et al., 2020). Process simulation research shows how event logs can support simulation-ready models (Camargo et al., 2022).

Each candidate model was evaluated using six technical criteria: fitness, precision, generalization, simplicity, stability, and runtime efficiency. Stability measures whether the model remains similar under bootstrap samples of the same event log. Runtime efficiency measures whether the pipeline is practical for iterative business use. In addition, the business interpretation index described in Section 3.3 was computed through KPI mapping. The final selection was evaluated under four preference profiles: balanced, compliance-centered, efficiency-centered, and managerial-clarity-centered. The use of event logs for software process mining demonstrates that quality attributes can be integrated into process interpretation beyond the original business workflow setting (Lu et al., 2014). Financial process mining studies further show that auditability and traceability are central when event evidence supports assurance and control decisions (Werner and Gehrke, 2015).

4.3 Preference Profiles

The balanced profile assigns moderate weights across technical quality and business interpretation. It represents a general enterprise analytics team seeking a reliable model for improvement discussion. The compliance-centered profile places greater weight on precision and exception visibility because false allowance of unobserved behavior may create regulatory risk. The efficiency-centered profile emphasizes runtime, stability, and cycle-time explanation because managers need rapid iteration. The managerial-clarity profile places greater weight on simplicity and interpretability because the model must support communication with nontechnical stakeholders. Configurable process modeling supports different requirements through roles and objects in a process model (La Rosa et al., 2008). Data analytics capability research also suggests that organizational value depends on the ability to combine technical resources with managerial routines (Ghasemaghaei and Calic, 2019).

These profiles are deliberately stylized. In practice, organizations should develop profiles through workshops involving process owners, data analysts, compliance staff, internal auditors, and information system managers. The value of the framework does not depend on one universal weight set. Its value lies in documenting the connection between stakeholder priorities and model selection. Local explanation methods illustrate how complex analytical outputs can be made accessible to users who need practical reasons for a recommendation (Ribeiro et al., 2016). The discipline of interpretable machine learning further argues that explanation quality should be judged by whether it supports human understanding and action (Doshi-Velez and Kim, 2017).

5. Results and Analysis

5.1 Comparative Model Selection Results

Table 3 reports the selected model under the balanced profile for each event-log scenario. The

results show that no single discovery pipeline dominates all operations. The order-to-cash log is best represented by an inductive miner after infrequent trace filtering, which balances fitness and precision while preserving the dominant order fulfillment structure. The procure-to-pay log is best represented by a split miner with timestamp repair, which better handles approval loops and supplier confirmation variants. The service-desk log is best represented by a heuristic miner with activity aggregation, which produces a compact and stable model suitable for high-volume ticket analysis.

The balanced profile improves the composite score relative to a default discovery baseline in all three scenarios. The improvement is largest for the service-desk log because the high exception share makes default discovery particularly sensitive to noise. The result is important for managerial use. It suggests that preference-aware selection does not merely make the model more elegant. It changes the analytical reliability of subsequent performance interpretation. Predictive analytics research in information systems distinguishes explanation from prediction, a distinction that is also important when process maps are used for future-oriented operational decisions (Shmueli and Koppius, 2011).

Table 3. Balanced-Profile Model Selection Results

Scenario	Selected pipeline	Fitness	Precision	BII	Composite score	Gain vs. default
Order-to-cash	Infrequent filtering + Inductive Miner	0.91	0.78	0.76	0.812	12.9%
Procure-to-pay	Timestamp repair + Split Miner	0.87	0.81	0.74	0.798	10.7%
Service desk	Activity aggregation + Heuristic Miner	0.89	0.75	0.80	0.824	17.8%

The selected models also differ in the type of insight they provide. In the order-to-cash scenario, the selected model identifies a rework loop between invoice correction and payment matching. In the procure-to-pay scenario, the selected model reveals that supplier confirmation delays are often preceded by nonstandard approval routing. In the service-desk scenario, the selected model highlights reassignment loops that are associated with service level breaches. These findings illustrate why technical model selection and business interpretation should be considered together. A model that fails to represent the relevant loop may understate the operational issue, while a model that overrepresents noise may exaggerate complexity. Business intelligence and analytics research shows that data-driven capabilities improve performance when they are embedded in organizational decision processes (Chen et al., 2012).

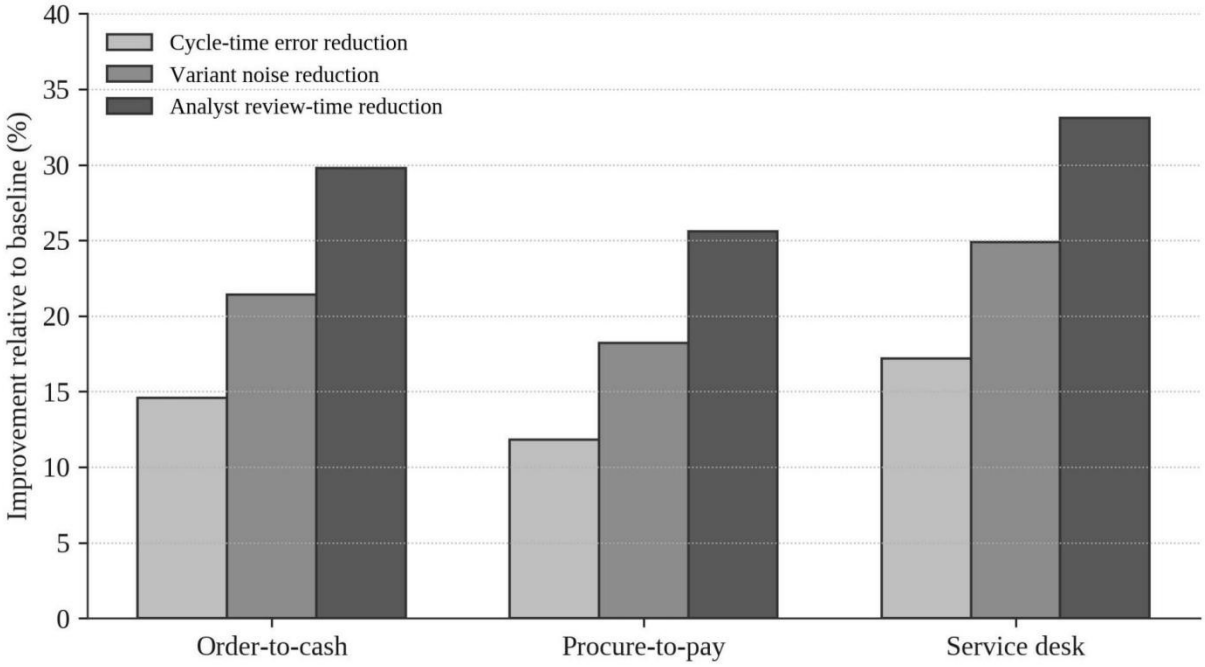


Figure 1. Improvement in Business Interpretation Outcomes under Preference-Aware Selection

Figure 1 shows three types of improvement relative to default discovery: cycle-time error reduction, variant noise reduction, and analyst review-time reduction. Cycle-time error reduction measures whether the selected model produces performance paths that align more closely with event-long duration measurements. Variant noise reduction measures whether the model avoids overemphasizing low-frequency paths that do not materially affect business performance. Analyst review-time reduction estimates the time saved when analysts inspect a more coherent process representation. The service-desk process benefits most because its initial event log contains the highest exception share and most frequent reassignment patterns.

5.2 Interpretation of Operational Performance

The order-to-cash result is also noteworthy. The selected model reduces cycle-time interpretation error by 14.6% and reduces analyst review time by 29.8%. This suggests that preference-aware model selection can support finance operations by improving the reliability of payment delay interpretation. Managers can

focus on invoice correction loops and credit release timing rather than debating whether the process map itself is an artifact of noisy discovery. In procure-to-pay, the improvement is more moderate but still meaningful because timestamp repair reduces false lead-time inflation caused by late system updates. Big data analytics capability studies indicate that process evidence creates value only when organizations possess the complementary resources to use it (Wamba et al., 2017).

These findings demonstrate that the business value of model selection should not be measured only by technical scores. A process model with a slightly lower fitness score may be more useful if it produces a more stable interpretation of cost, delay, or compliance. The result supports a broader view of process analytics as evidence construction. Event logs provide evidence, algorithms create representations, preference profiles guide selection, and managers interpret selected models as operational evidence. Organizational analytics capability research also confirms that managerial, technical, and data resources jointly determine whether analytics improves performance (Gupta and George, 2016).

5.3 Sensitivity to Preference Weights

Preference-aware analytics must be accompanied by sensitivity analysis because weights may vary across stakeholders. Figure 2 illustrates how the composite score changes as the weight assigned to precision increases. The high-precision model becomes preferred when the precision weight exceeds approximately 0.36. The balanced model performs best when precision is important but not dominant. The simple model performs well when precision weight is low and managerial readability is more important. Studies of big data analytics capabilities suggest that organizational capabilities mediate the pathway from analytics to innovation (Mikalef et al., 2019).

This result has two managerial interpretations. First, a process mining project should not claim that one model is best without specifying the preference profile. Second, disagreement among stakeholders may be productive because it reveals the decision context. If compliance staff prefer the high-precision model while operations managers prefer the balanced model, the organization should not simply average the two views without discussion. It should decide whether the immediate purpose is audit assurance, operational improvement, or executive communication. Each purpose can justify a different model. Research on data analytics competency further emphasizes that data quality and analytic skill interact to determine decision quality (Ghasemaghaei, 2021).

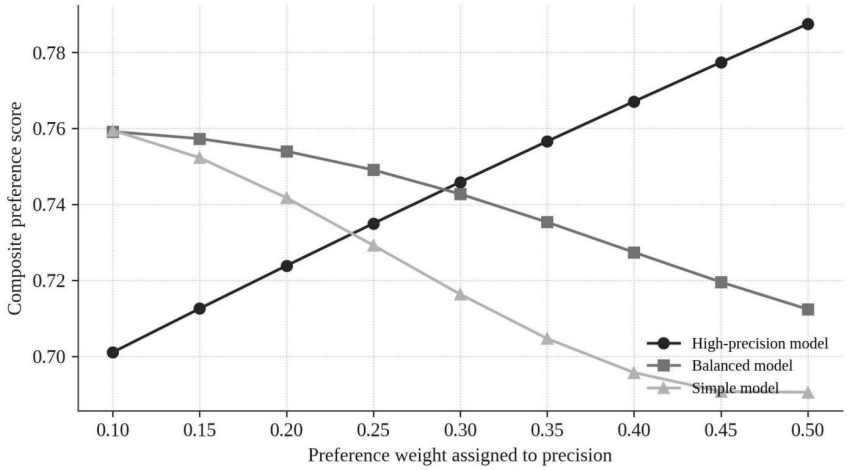


Figure 2. Sensitivity of Model Preference Scores to the Precision Weight

The sensitivity analysis also helps identify unstable recommendations. In the service-desk scenario, small changes in the weight assigned to simplicity may switch the selected model from a heuristic miner to an inductive miner. This instability is not a failure of the framework. It is useful evidence that the event log contains competing patterns. Managers should then review the two candidate models side by side and examine whether the difference reflects meaningful operational complexity or data quality problems. Research on predictive process monitoring identifies changing process behavior as a challenge (Ceravolo et al., 2024).

5.4 Preference Profiles and Recommended Managerial Use

Table 4 compares the four preference profiles. The balanced profile is appropriate when the process analytics team seeks a general-purpose model for improvement workshops. The compliance-centered profile is appropriate when exception visibility and auditability are more important than simplicity. The efficiency-centered profile is appropriate when quick iteration and runtime stability are required, such as weekly operational monitoring. The managerial-clarity profile is appropriate when the model will be presented to senior managers or cross-functional teams that need a concise representation of dominant process behavior.

The results show that preference profiles change the selected model in two of the three scenarios. This reinforces the claim that model selection is not a neutral technical step. For example, in procure-to-pay, the compliance-centered profile selects a more precise model that exposes rare approval deviations. The managerial-clarity profile selects a simpler model that suppresses those rare deviations and highlights the dominant approval chain. Both models can be legitimate, but they support different decisions. The compliance model is better for audit review. The clarity model is better for policy redesign workshops. Enterprise system auditing research suggests that reliable process evidence is particularly important when models are used for financial or compliance assurance (Jans et al., 2014).

Table 4. Preference Profiles and Managerial Use Cases

Preference profile	Highest-weighted criteria	Typical selected model	Recommended managerial use
Balanced	Fitness, precision, BII, simplicity	Stable mid-complexity model	General improvement diagnosis
Compliance-centered	Precision, exception visibility, stability	High-precision model	Audit, control, and regulatory review
Efficiency-centered	Runtime, stability, cycle-time explanation	Fast and robust model	Recurring operational monitoring
Managerial clarity	Simplicity, interpretability, BII	Simplified dominant-flow model	Executive communication and workshop facilitation

5.5 Business Interpretation Matrix

Figure 3 presents the business interpretation matrix across the three event-log scenarios. The order-to-cash process scores highest on cycle-time explanation because its selected model clearly separates standard fulfillment from invoice correction and payment exception handling. The procure-to-pay process scores highest on compliance because approval deviations and supplier confirmation paths are more visible after timestamp repair. The service-desk process scores highest on service reliability because reassignment loops and escalation patterns are well represented after activity aggregation.

The matrix demonstrates why business interpretation should be multidimensional. A model that is strong for compliance may not be equally strong for cost-to-serve interpretation. A model that explains cycle time may still require additional resource-level analysis to explain labor cost. This finding encourages analysts to avoid overly broad claims. Instead of stating that a selected process model is simply good, they should state which business interpretation it supports and where it remains limited. Process modeling guidelines similarly warn that clarity, correctness, and audience orientation should guide the presentation of process models (Mendling et al., 2010).

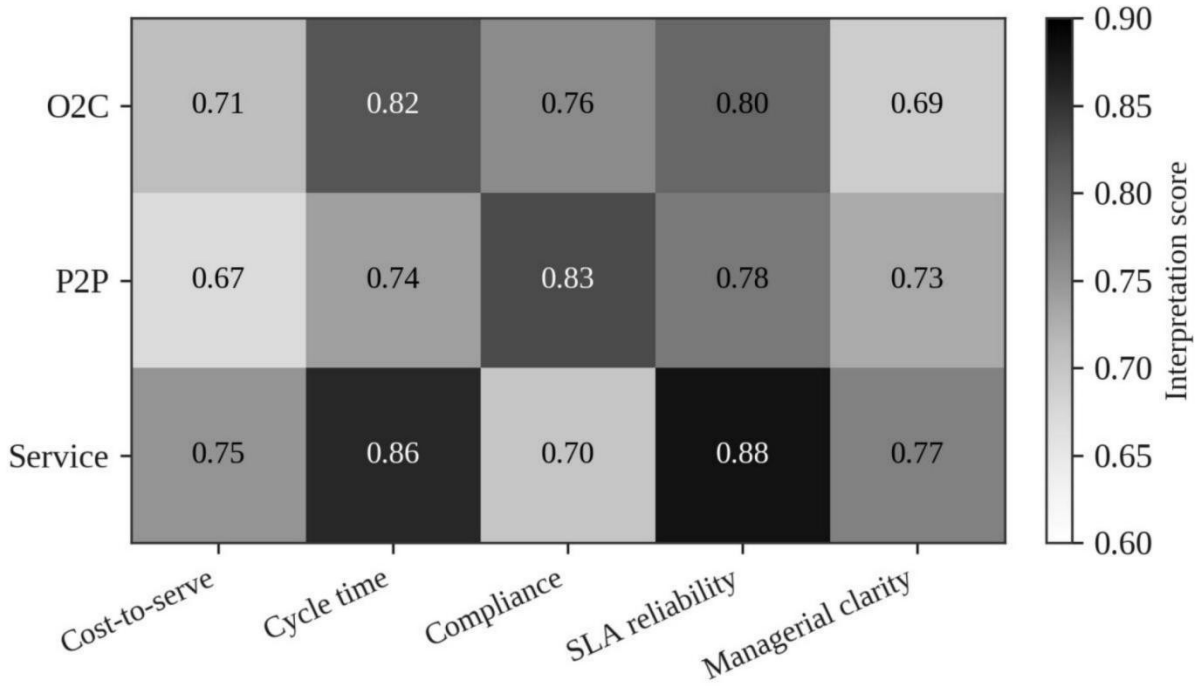


Figure 3. Business Interpretation Matrix for Selected Models across Enterprise Operations

5.6 Robustness Checks

Three robust checks were conducted. First, the candidate set was expanded by increasing noise-threshold granularity. The same balanced-profile selections were retained for order-to-cash and service-desk processes, while procure-to-pay switched between two split-miner variants with nearly identical scores. Second, metric normalization was changed from min-max scaling to rank-based scaling. The ranking of the top two candidates changed in the order-to-cash scenario, but the selected model remained within the same family of filtered inductive models. Third, the event logs were resampled through bootstrap sampling to evaluate stability. The selected models retained more than 86% structural similarity across resamples in all scenarios. Reviews of artificial intelligence in industrial information systems show that robust analytical

design is necessary when AI-supported tools are introduced into operational settings (Zhang and Lu, 2021). Management analytics research also stresses that analytical systems should be evaluated by their contribution to decision improvement rather than by technical sophistication alone (Lu, 2021).

These robust checks suggest that the framework is not overly dependent on one data transformation or one exact candidate set. However, they also show that preference-aware selection should be accompanied by transparent reporting. If two candidates have nearly equal scores, both should be presented to stakeholders. A forced single-model recommendation may create a false sense of precision. In enterprise operations, analytical humility is preferable to overconfident automation. Bibliometric evidence on management analytics indicates that the field increasingly connects quantitative modeling, information systems, and managerial decision-making (Lu et al., 2024a). Recent work on management analytics further argues that modern business practice requires disciplined translation from data output to managerial action (Lu et al., 2024b).

6. Managerial Implications

The first implication is that process mining governance should include explicit model selection rules. Many organizations treat process discovery as a software output: users load a log, choose adefault algorithm, and discuss the resulting map. This practice is risky because it hides assumptions about filtering, algorithm selection, and model quality. A governance process should require analysts to define the business question, construct a candidate portfolio, specify the preference profile, document thresholds, and report sensitivity. This does not make the project bureaucratic. It makes the project auditable and repeatable. Industry 4.0 research highlights the need for integrated digital governance when operational data flows across machines, platforms, and organizational functions (Lu, 2025). Blockchain applications in Industry 4.0 illustrate how traceability mechanisms can strengthen trust in distributed operational records (Chen et al., 2024).

The second implication is that business users should participate in weight selection. Technical teams understand fitness, precision, and runtime, but process owners understand whether exception visibility, communication simplicity, or cycle-time explanation matters more for the decision at hand. A useful process analytics project should therefore include a short preference elicitation workshop. During that workshop, stakeholders should discuss the consequences of overfitting, underfitting, hiding rare variants, and presenting excessive complexity. The resulting weights should be documented in the analysis report. Information systems research on blockchain implementation shows that technological transparency must be matched with organizational readiness and governance (Lu, 2022). Secure IoT integration research also demonstrates that trace data can create value only when cybersecurity and data integrity are managed explicitly (Xu et al., 2021).

The third implication is that organizations should distinguish between process models for audit and process models for improvement. An audit-oriented model should preserve deviations and demonstrate why certain paths are nonstandard. An improvement-oriented model may need to simplify variants so that managers can identify the major bottlenecks and redesign work. A communication-oriented model may need even greater simplicity. The same event log can support all three purposes, but not necessarily through the same selected model. This distinction reduces conflict between compliance teams and operational teams because it recognizes that different questions require different analytical representations. Service process mining in healthcare indicates that managerial interpretation should distinguish clinically or operationally meaningful exceptions from noise (Rebuge and Ferreira, 2012). IoT cybersecurity research further supports the need to protect event data that flows through connected enterprise infrastructures (Lu and Xu, 2019).

The fourth implication is that process mining results should be linked to measurable business indicators. A model should not end with a visual map. It should be connected to cycle-time distributions, rework frequencies, handoff counts, SLA breaches, cost drivers, and compliance events. This connection turns

process discovery into business performance interpretation. It also helps managers decide whether an apparent process problem is financially material. A visually complex variant may not deserve attention if it affects very few cases and does not create cost or risk. A simple-looking loop may deserve urgent attention if it affects high-value orders or regulated transactions. Industry 4.0 research shows that cyber-physical integration expands the range of operational traces available for performance analysis (Lu, 2017). FinTech research similarly demonstrates that digital platforms increasingly depend on auditable data flows, risk controls, and analytics-driven governance (Kou and Lu, 2025).

The fifth implication is that automation should support, not replace, managerial judgment. Preference-aware scoring provides a disciplined way to compare models, but final interpretation still requires domain knowledge. Managers know which exceptions are legitimate, which delays are unavoidable, and which policy deviations indicate real control problems. The framework therefore positions analytics as a structured conversation between event-log evidence and managerial reasoning. Blockchain-enabled internal auditing research also shows that traceability technologies can support assurance when operational evidence must be verified across systems (Wu et al., 2025).

7. Limitations and Future Research

This study has several limitations. First, numerical study uses calibrated event-log scenarios rather than proprietary company logs. This design supports transparency and allows the framework to be described clearly, but it cannot capture all organizational complexities. Future research should apply the framework to real enterprise logs from finance operations, logistics, healthcare administration, public services, and customer support. Real-world validation would allow researchers to test whether preference-aware selection improves actual managerial decisions, not only model scores.

Second, the preference weights used in this study are stylized. They represent plausible stakeholder priorities, but they are not derived from a formal elicitation study. Future research could compare weight elicitation methods, including analytic hierarchy process, swing weighting, Delphi panels, and interactive decision workshops. It would also be valuable to study how stakeholder groups negotiate weights when their objectives conflict. For example, compliance teams and operations teams may assign very different values to exception visibility and simplicity.

Third, the business interpretation index aggregates several dimensions that may be context dependent. The same weights should not be used in every process. In regulated banking, compliance visibility may dominate. In a call center, service reliability may dominate. In manufacturing planning, cost-to-serve and resource utilization may matter more. Future studies could develop industry-specific interpretation indices and test whether they improve decision quality.

Fourth, the framework assumes that candidate model quality can be evaluated after discovery. Future research may integrate preference information earlier in the pipeline, allowing the search procedure itself to generate models that are closer to stakeholder priorities. This would connect preference-aware business analytics with multi-objective optimization and automated machine learning. However, such automation should remain interpretable because business users need to understand why a model was selected.

Fifth, the study focuses on process discovery and performance interpretation. Future work could extend the framework to predictive process monitoring, prescriptive intervention, robotic process automation prioritization, and digital twin simulation. In each extension, the same principle applies: technical models should be selected and interpreted in relation to business preferences.

8. Conclusion

This article developed a preference-aware process analytics framework for enterprise operations. Building on the research direction of automated process discovery configuration, the study reframed process discovery as a business data analytics problem involving event-log evidence, candidate model portfolios, multi-criteria model selection, and performance interpretation. The framework recognizes that process models are not neutral representations. They are analytical choices shaped by preprocessing rules, discovery algorithms, metric trade-offs, and stakeholder priorities. The numerical study across order-to-cash, procure-to-pay, and service-desk processes showed that preference-aware model selection improves composite interpretation scores, reduces analyst review time, and creates a clearer link between process models and operational KPIs. The results also showed that different preference profiles can lead to different model selections. This does not weaken the approach. It strengthens the argument that organizations should explicitly state the purpose of their process analytics project before selecting a model. A model for audit assurance may differ from a model for managerial communication, and both may differ from a model for recurring operational monitoring.

The study contributes to business and data analytics by bridging a gap between technical process mining and managerial decision-making. It offers a practical structure for governing process mining projects, documenting selection assumptions, and translating event-log evidence into business performance interpretation. For managers, the main message is straightforward: do not ask only which process model has the best technical score. Ask which model best supports the business decision that the organization needs to make.

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Author Contributions

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Conflicts of Interest

The authors declare no conflict of interest.

Ethical Approval and Consent

Not applicable. This study did not involve human participants, personal data, or animals.

Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Declaration of Generative AI Use

The authors did not use generative AI tools in the preparation of this manuscript.

References

Abrehdari, S. H. (2025). Leveraging the process mining technique to optimize data preparation time in a database used as an automated data delivery center. MethodsX, 15, 103428. https://doi.org/10.1016/j.mex.2025.103428

Akiba, T., Sano, S., Yanase, T., Ohta, T., & Koyama, M. (2019). Optuna: A next-generation hyperparameter optimization framework. In Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (pp. 2623–2631). https://doi.org/10.1145/3292500.3330701

Andrews, R., van Dun, C. G. J., Wynn, M. T., Kratsch, W., Röglinger, M., & ter Hofstede, A. H. M. (2020). Quality-informed semi-automated event log generation for process mining. Decision Support Systems, 132, 113265. https://doi.org/10.1016/j.dss.2020.113265

Barredo Arrieta, A., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., et al. (2020). Explainable artificial intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. Information Fusion, 58, 82–115. https://doi.org/10.1016/j.inffus.2019.12.012

Beerepoot, I., van de Weerd, I., & Reijers, H. A. (2019). Business process improvement activities: Differences in organizational size, culture, and resources. In Business Process Management (pp. 402–418). Springer. https://doi.org/10.1007/978-3-030-26619-6_26

Bertsimas, D., & Kallus, N. (2020). From predictive to prescriptive analytics. Management Science, 66(3), 1025–1044. https://doi.org/10.1287/mnsc.2018.3253

Bolt, A., de Leoni, M., & van der Aalst, W. M. P. (2016). Scientific workflows for process mining: Building blocks, scenarios, and implementation. International Journal on Software Tools for Technology Transfer, 18(6), 607–628. https://doi.org/10.1007/s10009-015-0399-5

Buijs, J. C. A. M., van Dongen, B. F., & van der Aalst, W. M. P. (2012). On the role of fitness, precision, generalization and simplicity in process discovery. In On the Move to Meaningful Internet Systems: OTM 2012 (pp. 305–322). Springer. https://doi.org/10.1007/978-3-642-33606-5_19

Camargo, M., Dumas, M., & González-Rojas, O. (2022). Learning accurate business process simulation models from event logs via automated process discovery and deep learning. In Advanced Information Systems Engineering (pp. 55–71). Springer. https://doi.org/10.1007/978-3-031-07472-1_4

Ceravolo, P., Comuzzi, M., De Weerdt, J., Di Francescomarino, C., & Maggi, F. M. (2024). Predictive process monitoring: Concepts, challenges, and future research directions. Process Science, 1, 2. https://doi.org/10.1007/s44311-024-00002-4

Chen, H., Chiang, R. H. L., & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. MIS Quarterly, 36(4), 1165–1188. https://doi.org/10.2307/41703503

Chen, Y., Lu, Y., Bulysheva, L., & Kataev, M. Y. (2024). Applications of blockchain in Industry 4.0: A review. Information Systems Frontiers, 26(5), 1715–1729. https://doi.org/10.1007/s10796-022-10248-7

Comuzzi, M., Ko, J., & Maggi, F. M. (2025). A language to model and simulate data quality issues in process mining. ACM Journal of Data and Information Quality, 17(2), Article 6, 1–36. https://doi.org/10.1145/3743144

Dakic, D., Stefanovic, D., Vuckovic, T., Zizakov, M., & Stevanov, B. (2023). Event log data quality issues and solutions. Mathematics, 11(13), 2858. https://doi.org/10.3390/math11132858

de Leoni, M., & van der Aalst, W. M. P. (2013). Aligning event logs and process models for multi-perspective conformance checking: An approach based on integer linear programming. In Business Process Management (pp. 113–129). Springer. https://doi.org/10.1007/978-3-642-40176-3_10

De Roock, E., & Martin, N. (2022). Process mining in healthcare – An updated perspective on the state of the art. Journal of Biomedical Informatics, 127, 103995. https://doi.org/10.1016/j.jbi.2022.103995

Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Transactions on Evolutionary Computation, 6(2), 182–197. https://doi.org/10.1109/4235.996017

Di Francescomarino, C., Ghidini, C., Maggi, F. M., & Milani, F. (2018). Predictive process monitoring methods: Which one suits me best? In Business Process Management (pp. 462–479). Springer. https://doi.org/10.1007/978-3-319-98648-7_27

Doshi-Velez, F., & Kim, B. (2017). Towards a rigorous science of interpretable machine learning. arXiv. https://doi.org/10.48550/arXiv.1702.08608

Dumas, M., La Rosa, M., Mendling, J., & Reijers, H. A. (2013). Fundamentals of business process management. Springer. https://doi.org/10.1007/978-3-642-33143-5

Emmerich, M. T. M., & Deutz, A. H. (2018). A tutorial on multiobjective optimization: Fundamentals and evolutionary methods. Natural Computing, 17(3), 585–609. https://doi.org/10.1007/s11047-018-9685-y

Fahrenkrog-Petersen, S. A., van der Aa, H., & Weidlich, M. (2023). Optimal event log sanitization for privacy-preserving process mining. Data & Knowledge Engineering, 145, 102175. https://doi.org/10.1016/j.datak.2023.102175

Feurer, M., & Hutter, F. (2019). Hyperparameter optimization. In Automated Machine Learning (pp. 3–33). Springer. https://doi.org/10.1007/978-3-030-05318-5_1

Ghasemaghaei, M. (2021). Understanding the impact of big data on firm performance: The necessity of conceptually differentiating among big data characteristics. International Journal of Information Management, 57, 102055. https://doi.org/10.1016/j.ijinfomgt.2019.102055

Ghasemaghaei, M., & Calic, G. (2019). Does big data enhance firm innovation competency? The mediating role of data-driven insights. Journal of Business Research, 104, 69–84. https://doi.org/10.1016/j.jbusres.2019.07.006

Greco, S., Ehrgott, M., & Figueira, J. R. (Eds.). (2016). Multiple criteria decision analysis: State of the art surveys. Springer. https://doi.org/10.1007/978-1-4939-3094-4

Guidotti, R., Monreale, A., Ruggieri, S., Turini, F., Giannotti, F., & Pedreschi, D. (2018). A survey of methods for explaining black box models. ACM Computing Surveys, 51(5), Article 93, 1–42. https://doi.org/10.1145/3236009

Gupta, M., & George, J. F. (2016). Toward the development of a big data analytics capability. Information & Management, 53(8), 1049–1064. https://doi.org/10.1016/j.im.2016.07.004

Hanga, K. M., Kovalchuk, Y., & Gaber, M. M. (2020). A graph-based approach to interpreting recurrent neural networks in process mining. IEEE Access, 8, 172923–172938. https://doi.org/10.1109/ACCESS.2020.3025999

Hutter, F., Hoos, H. H., & Leyton-Brown, K. (2011). Sequential model-based optimization for general algorithm configuration. In Learning and Intelligent Optimization (pp. 507–523). Springer. https://doi.org/10.1007/978-3-642-25566-3_40

Ileri, I., Gurgen Erdogan, T., & Kolukisa-Tarhan, A. (2025). Privacy for process mining: A systematic literature review. IEEE Access, 13, 83171–83194. https://doi.org/10.1109/ACCESS.2025.3568889

Jalayer, A., Kahani, M., Pourmasoumi, A., & Beheshti, A. (2022). HAM-Net: Predictive business process monitoring with a hierarchical attention mechanism. Knowledge-Based Systems, 236, 107722. https://doi.org/10.1016/j.knosys.2021.107722

Jans, M., Alles, M. G., & Vasarhelyi, M. A. (2014). A field study on the use of process mining of event logs as an analytical procedure in auditing. The Accounting Review, 89(5), 1751–1773. https://doi.org/10.2308/accr-50807

Kou, G., & Lu, Y. (2025). FinTech: A literature review of emerging financial technologies and applications. Financial Innovation, 11, Article 1. https://doi.org/10.1186/s40854-024-00668-6

La Rosa, M., Dumas, M., ter Hofstede, A. H. M., Mendling, J., & Gottschalk, F. (2008). Beyond control-flow: Extending business process configuration to roles and objects. In Conceptual Modeling – ER 2008 (pp. 199–215). Springer. https://doi.org/10.1007/978-3-540-87877-3_16

Leemans, S. J. J., Fahland, D., & van der Aalst, W. M. P. (2013). Discovering block-structured process models from event logs: A constructive approach. In Applications and Theory of Petri Nets and Concurrency (pp. 311–329). Springer. https://doi.org/10.1007/978-3-642-38697-8_17

Lipton, Z. C. (2018). The mythos of model interpretability. Queue, 16(3), 31–57. https://doi.org/10.1145/3236386.3241340

Lopez-Ibanez, M., Dubois-Lacoste, J., Cáceres, L. P., Birattari, M., & Stützle, T. (2016). The irace package: Iterated racing for automatic algorithm configuration. Operations Research Perspectives, 3, 43–58. https://doi.org/10.1016/j.orp.2016.09.002

Lu, X., Mans, R. S., Fahland, D., & van der Aalst, W. M. P. (2014). Conformance checking in healthcare based on partially ordered event data. In Proceedings of the 2014 IEEE Emerging Technology and Factory Automation (ETFA) (pp. 1–8). IEEE. https://doi.org/10.1109/ETFA.2014.7005060

Lu, Y. (2017). Industry 4.0: A survey on technologies, applications and open research issues. Journal of Industrial Information Integration, 6, 1–10. https://doi.org/10.1016/j.jii.2017.04.005

Lu, Y. (2019). Artificial intelligence: A survey on evolution, models, applications and future trends. Journal of Management Analytics, 6(1), 1–29. https://doi.org/10.1080/23270012.2019.1570365

Lu, Y. (2021). Technological innovation and the emergence of a new interdisciplinary field: Management Analytics. Nanotechnologies in Construction, 13(3), 181–192. https://doi.org/10.15828/2075-8545-2021-13-3-181-192

Lu, Y. (2022). Implementing blockchain in information systems: A review. Enterprise Information Systems, 16(12), Article 2008513. https://doi.org/10.1080/17517575.2021.2008513

Lu, Y. (2025). The current status and developing trends of Industry 4.0: A review. Information Systems Frontiers, 27(1), 215–234. https://doi.org/10.1007/s10796-021-10221-w

Lu, Y., Ivanov, L. A., Wang, F., Pisarenko, Zh. V., & Ye, C. (2024a). Management analytics: A bibliometric analysis. Nanotechnologies in Construction, 16(3), 257–266. https://doi.org/10.15828/2075-8545-2024-16-3-257-266

Lu, Y., Pisarenko, Zh. V., Yang, L., Ivanov, L. A., & Ye, C. (2024b). Advancing decision-making: The role of management analytics in modern business practices. Nanotechnologies in Construction, 16(5), 431–440. https://doi.org/10.15828/2075-8545-2024-16-5-431-440

Lu, Y., & Xu, L. D. (2019). Internet of Things (IoT) cybersecurity research: A review of current research topics. IEEE Internet of Things Journal, 6(2), 2103–2115. https://doi.org/10.1109/JIOT.2018.2869847

Maggi, F. M., Westergaard, M., Montali, M., & van der Aalst, W. M. P. (2012). Runtime verification of LTL-based declarative process models. In Runtime Verification (pp. 131–146). Springer. https://doi.org/10.1007/978-3-642-29860-8_11

Malinova, M., Leopold, H., & Mendling, J. (2015). An explorative study for process map design. In Information Systems Engineering in Complex Environments (pp. 36–51). Springer. https://doi.org/10.1007/978-3-319-19270-3_3

Mannhardt, F. (2022). Responsible process mining. In Process Mining Handbook (pp. 373–401). Springer. https://doi.org/10.1007/978-3-031-08848-3_12

Mannhardt, F., de Leoni, M., Reijers, H. A., & van der Aalst, W. M. P. (2016). Balanced multi-perspective checking of process conformance. Computing, 98(4), 407–437. https://doi.org/10.1007/s00607-015-0441-1

Marcus, L., Schmid, S. J., Friedrich, F., Röglinger, M., & Grindemann, P. (2026). Navigating the landscape of organizational process mining setups: A taxonomy approach. Business & Information Systems Engineering, 68(1), 137–158. https://doi.org/10.1007/s12599-024-00908-0

Mardani, A., Jusoh, A., Nor, K. M. D., Khalifah, Z., Zakwan, N., & Valipour, A. (2015). Multiple criteria decision-making techniques and their applications: A review of the literature from 2000 to 2014. Economic Research-Ekonomska Istraživanja, 28(1), 516–571. https://doi.org/10.1080/1331677X.2015.1075139

Márquez-Chamorro, A. E., Resinas, M., & Ruiz-Cortés, A. (2018). Predictive monitoring of business processes: A survey. IEEE Transactions on Services Computing, 11(6), 962–977. https://doi.org/10.1109/TSC.2017.2772256

Mendling, J., Reijers, H. A., & van der Aalst, W. M. P. (2010). Seven process modeling guidelines. Information and Software Technology, 52(2), 127–136. https://doi.org/10.1016/j.infsof.2009.08.004

Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019). Big data analytics capabilities and innovation: The mediating role of dynamic capabilities and moderating effect of the environment. British Journal of Management, 30(2), 272–298. https://doi.org/10.1111/1467-8551.12343

Neu, D. A., Lahann, J., & Fettke, P. (2022). A systematic literature review on state-of-the-art deep learning methods for process prediction. Artificial Intelligence Review, 55, 801–827. https://doi.org/10.1007/s10462-021-09960-8

Opricovic, S., & Tzeng, G. H. (2004). Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. European Journal of Operational Research, 156(2), 445–455. https://doi.org/10.1016/S0377-2217(03)00020-1

Pradhan, S. K., Jans, M., & Martin, N. (2025). Getting the data in shape for your process mining analysis: An in-depth analysis of the pre-analysis stage. ACM Computing Surveys, 57(6), Article 159, 1–37. https://doi.org/10.1145/3712587

Rebuge, A., & Ferreira, D. R. (2012). Business process analysis in healthcare environments: A methodology based on process mining. Information Systems, 37(2), 99–116. https://doi.org/10.1016/j.is.2011.01.003

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

Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). Why should I trust you? Explaining the predictions of any classifier. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (pp. 1135–1144). https://doi.org/10.1145/2939672.2939778

Roy, B. (1991). The outranking approach and the foundations of ELECTRE methods. Theory and Decision, 31(1), 49–73. https://doi.org/10.1007/BF00134132

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

Saaty, T. L. (2008). Decision making with the analytic hierarchy process. International Journal of Services Sciences, 1(1), 83–98. https://doi.org/10.1504/IJSSCI.2008.017590

Shameli-Sendi, A. (2020). An efficient security data-driven approach for implementing risk assessment. Journal of Information Security and Applications, 54, 102593. https://doi.org/10.1016/j.jisa.2020.102593

Shmueli, G., & Koppius, O. R. (2011). Predictive analytics in information systems research. MIS Quarterly, 35(3), 553–572. https://doi.org/10.2307/23042796

Stein Dani, V., Dees, M., Leopold, H., Busch, K., Beerepoot, I., van der Werf, J. M., & Reijers, H. A. (2025). Event log extraction for process mining using large language models. In 30th International Conference on Cooperative Information Systems (CoopIS 2024) (pp. 56–72). Springer. https://doi.org/10.1007/978-3-031-81375-7_4

Suriadi, S., Andrews, R., ter Hofstede, A. H. M., & Wynn, M. T. (2017). Event log imperfection patterns for process mining: Towards a systematic approach to cleaning event logs. Information Systems, 64, 132–150. https://doi.org/10.1016/j.is.2016.07.011

Tax, N., Verenich, I., La Rosa, M., & Dumas, M. (2017). Predictive business process monitoring with LSTM neural networks. In Advanced Information Systems Engineering (pp. 477–492). Springer. https://doi.org/10.1007/978-3-319-59536-8_30

Thornton, C., Hutter, F., Hoos, H. H., & Leyton-Brown, K. (2013). Auto-WEKA: Combined selection and hyperparameter optimization of classification algorithms. In Proceedings of the 19th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (pp. 847–855). https://doi.org/10.1145/2487575.2487629

van der Aalst, W. M. P. (2023). Object-centric process mining: Unraveling the fabric of real processes. Mathematics, 11(12), 2691. https://doi.org/10.3390/math11122691

van der Aalst, W. M. P., Adriansyah, A., de Medeiros, A. K. A., Arcieri, F., Baier, T., Blickle, T., et al. (2012). Process mining manifesto. In F. Daniel, K. Barkaoui, & S. Dustdar (Eds.), Business Process Management Workshops (pp. 169–194). Springer. https://doi.org/10.1007/978-3-642-28108-2_19

vom Brocke, J., Baier, M. S., Schmiedel, T., Stelzl, K., Röglinger, M., & Wehking, C. (2021). Context-aware business process management: Method assessment and selection. Business & Information Systems Engineering, 63(5), 533–550. https://doi.org/10.1007/s12599-021-00685-0

Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. Journal of Business Research, 70, 356–365. https://doi.org/10.1016/j.jbusres.2016.08.009

Werner, M., & Gehrke, N. (2015). Multilevel process mining for financial audits. IEEE Transactions on Services Computing, 8(6), 820–832. https://doi.org/10.1109/TSC.2015.2457907

Wu, H. P., Liu, Z., Dong, H. Y., Lu, Y., & Xu, L. D. (2025). Revolutionizing internal auditing: Harnessing the power of blockchain. Enterprise Information Systems, 19(1–2), 2448003. https://doi.org/10.1080/17517575.2024.2448003

Xu, L. D., Lu, Y., & Li, L. (2021). Embedding blockchain technology into IoT for security: A survey. IEEE Internet of Things Journal, 8(13), 10452–10473. https://doi.org/10.1109/JIOT.2021.3060508

Zhang, C., & Lu, Y. (2021). Study on artificial intelligence: The state of the art and future prospects. Journal of Industrial Information Integration, 23, 100224. https://doi.org/10.1016/j.jii.2021.100224

Zheng, X. R., & Lu, Y. (2022). Blockchain technology: Recent research and future trend. Enterprise Information Systems, 16(12), 1939895. https://doi.org/10.1080/17517575.2021.1939895