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Causal Process Mining for Temporal Deviations in Business Event Flows

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Abstract. Efficient management of business processes is crucial in dynamic environments. Temporal deviations in execution times can affect workflows. They also increase costs and reduce service quality. Traditional process analysis methods generally rely on correlations. They do not establish causal relationships that explain these deviations. Existing approaches face challenges in identifying the underlying causes of temporal deviations. This difficulty limits the ability to apply precise interventions. Without a causal understanding, corrective actions may prove ineffective. They often address symptoms rather than underlying causes. This study integrates process mining with causal inference. The objective is to explain the factors that generate temporal deviations in enterprise workflows at the variant level. Causal discovery techniques are applied LiNGAM, PC, and GES. Event logs are grouped by variant and stratified into temporal-deviation clusters. This procedure identifies critical activities. Directed acyclic graphs DAG are also recovered to quantify their impact on delays. In addition, alternative scenarios are simulated using the $\mathrm{do}(\cdot)$ operator. These interventions provide actionable information for optimization. The methodology was validated with a dataset of 562 planning instances from a payment-processing company. The results identified causal relationships consistent with the learned DAGs. Among them, the impact of scheduled hours and complexity level on execution times. This work integrates process mining and causal inference. The result is a framework for data-driven decision-making in operational process management. The proposal improves the interpretability of temporal deviations. It also enables the design of more precise interventions. It contributes to establishing a methodological foundation for continuous improvement through causal analysis.

1 Introduction

In dynamic, competitive environments [1] organizations must manage their business processes effectively to achieve strategic objectives. Controlling operational performance is

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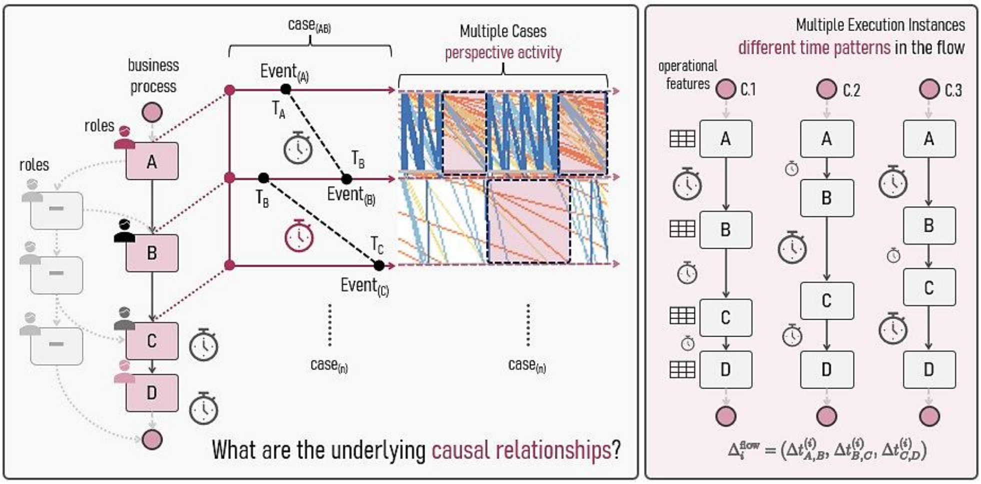

Fig. 1. Visual characterization of temporal deviations and their possible underlying causal relationships in business processes.

essential, particularly the execution times of activities. Within this framework, process mining, complemented by causal inference techniques, provides tools to identify and understand deviations.

As shown in Figure 1, temporal deviations appear in repeated executions of the same process. Multiple nominally identical instances are observed, but with distinct temporal patterns. This variability makes it difficult to identify and explain causal relationships, especially when roles, activities, and operational characteristics of the process interact.

Despite detailed planning of activities and schedules, temporal deviations persist [14]. Their effects are adverse: they increase operating costs, introduce delays, and reduce service quality. They also affect collaboration among roles [2]. Traditional methods rely on correlations [3, 4]. They do not clearly establish cause-and-effect relationships. This limitation reduces the ability to implement effective and timely corrective actions [5].

To address this problem, the present work proposes an integrated methodology. It combines process mining [9] with causal machine learning techniques [6]. The main objective is to identify and analyze cause-effect relationships associated with temporal deviations [7, 8]. The analysis operates at the variant level and uses stratification into temporal-deviation clusters. This favors interpretability and enables the design of interventions.

The specific objectives are: (***i***) to integrate process mining with advanced causal machine learning techniques; (***ii***) to identify causal relationships that explain temporal deviations in business processes; and (***iii***) to provide a framework for well-founded and timely managerial interventions, supported by clear and robust causal analysis.

In line with the above, this article poses the following research questions:

1. ***RQ*₁** How can process mining be integrated with causal machine learning techniques to identify specific causes of temporal deviations at the variant and cluster levels?

2. ***RQ*₂** What are the key causal relationships associated with the temporal deviations observed in business processes?

3. ***RQ*3** To what extent does causal understanding improve the quality and effectiveness of managerial decisions and interventions in the face of temporal deviations?

The organization of the document is as follows. *Preliminaries* present the key concepts (2). *Related Work* reviews prior studies (3). *Proposed Methodology* describes the approach based on process mining and causal inference (4). The *Results* are then reported (5), followed by the *Discussion* (6) and the *Conclusions* (7).

2 Preliminaries

Below, the essential concepts and notations that underpin the causal analysis developed in this study are presented, along with their respective formal definitions.

Definition 2.1 (Business Process Model). Let a business process model be defined as the tuple $P = (\mathcal{A}, <)$, where $\mathcal{A}$ is a finite set of activities and $<$ establishes the precedence relationship among them. Each case $c \in C$ generates a trace σ, represented by the sequence of executed activities with their respective timestamps $\sigma_i = \left((a_1, t^i_{a_1}), (a_2, t^i_{a_2}), \ldots, (a_n, t^i_{a_n})\right)$.

Here, $t^i_{a_k}$ is the timestamp of a_k in the case c_i. The set of all traces is denoted by Σ. A process variant is an equivalence class over Σ, determined by the sequence of activities. The projection operator act is defined as $\operatorname{act}(\sigma_i) = \langle a_1, a_2, \ldots, a_n \rangle$. Two traces σ_p, σ_q belong to the same variant v_j if and only if $\operatorname{act}(\sigma_p) = \operatorname{act}(\sigma_q)$. The set of variants is denoted by $\mathcal{V} = \{v_1, v_2, \ldots, v_k\}$.

Definition 2.2 (Temporal Deviation). The time interval between two consecutive activities a_j, a_{j+1} in σ_i is given by $\Delta t^i_{a_j a_{j+1}} = t^i_{a_{j+1}} - t^i_{a_j}$. The temporal deviation is obtained by comparing each $\Delta t^i_{a_j a_{j+1}}$ with the average interval $\overline{\Delta t_{a_j a_{j+1}}}$, forming the set $\Delta_{a_j a_{j+1}} = \left\{\Delta t^i_{a_j a_{j+1}} - \overline{\Delta t_{a_j a_{j+1}}} : i = 1, \ldots, m\right\}$.

Definition 2.3 (Average Causal Effect (ATE)). It is the expected average change in Y when, for the same population, X is exogenously set to (x') instead of (x); it is written as $\operatorname{ATE}(x', x) = \mathbb{E}[Y \mid do(X = x')] - \mathbb{E}[Y \mid do(X = x)]$ or, in potential-outcomes terms, $\mathbb{E}[Y(x') - Y(x)]$ with $Y_{(x)}$ denoting the outcome that a unit would have if X were set to x [26]. The observational difference $(\mathbb{E}[Y \mid X = x'] - \mathbb{E}[Y \mid X = x])$ compares groups that naturally take those values of X and may reflect other differences between them; the ATE answers what would occur under an exogenous manipulation of X.

Definition 2.4 (Causal Intervention). A $do(X = x)$ intervention externally sets X to the value x, severing all influences pointing into X; in structural models it is equivalent to replacing the structural equation for X with the assignment $X := x$, and in a dag to removing the incoming edges to X. The distribution $P(Y \mid do(X = x))$ describes the behavior of Y under that manipulation and typically differs from $P(Y \mid X = x)$ because the latter reflects who has $X = x$ in the observed data, not the result of forcing $X = x$.

3 Related Work

3.1 Temporal Deviations in Business Processes

Recent work on temporal deviations in business processes has followed two main lines: on the one hand, the detection and representation of timing patterns; on the other, the search for causal relationships to guide intervention decisions.

Within the family of temporal signatures, Böhmer and Rinderle-Ma [13] compare historical and current process behavior to enable early anomaly detection. Janina et al. [14] extend this idea with signatures centered on the intervals between consecutive activities. These studies increase sensitivity to temporal changes, although their scope narrows as trace length and the structural complexity of the process grow.

Regarding the representation of constraints, Pereira and Varajão [11] introduce specific temporal links in modeling languages. Senderovich et al. [12] propose the Temporal Network Representation (TNR) to capture relationships between activities with probabilistic support. Zhao et al. [17] present a temporal hierarchical model (TH-BPM) that organizes these constraints at different levels. These proposals offer an expressive framework; nevertheless, variability across instances and scalability remain challenges in scenarios with pronounced heterogeneity.

In operational monitoring and uncertainty management, Rogge-Solti and Kasneci [10] apply Bayesian methods to handle noise and complex dependencies in dynamic contexts. Richter and Seidl [15] introduce TESSERACT for real-time monitoring via exponential moving averages, and Asma et al. [19] incorporate metrics such as latency and temporal capacity. These techniques facilitate continuous process surveillance, although their performance depends on data quality and may degrade under abrupt changes.

Another line exploits temporal features for anomaly detection: Hsu et al. [16] identify irregular instances via contextualized activity-level durations (k-nearest neighbors), while Mavroudopoulos and Gounaris [18] show that proximity-based variants generalize to multi-dimensional trace similarity and often outperform simpler baselines, albeit with degradation in high-dimensional spaces.

3.2 Causality Business Processes

Qafari and Van der Aalst [20, 23] propose structural equation models integrated with algorithms such as GFCI to identify root causes in performance and compliance issues. In a similar vein, Luo et al. [21, 22] combine process mining and causal discovery through the ACLP framework and the SMMB algorithm, focusing on identifying causes in complex and dynamic processes. Both approaches stand out for offering effective methods to identify root causes, although they face common limitations related to reliance on expert knowledge and the difficulty of handling high variability in complex structures [27].

4 Proposed Method

The proposed methodology, illustrated in Figure 2, addresses the causal analysis of temporal deviations by focusing on specific variants of the business process. This approach differs from previous methods mentioned in Section 3.1, which analyze all log traces together. By studying variants individually, Simpson's paradox, where clear trends in subgroups disappear

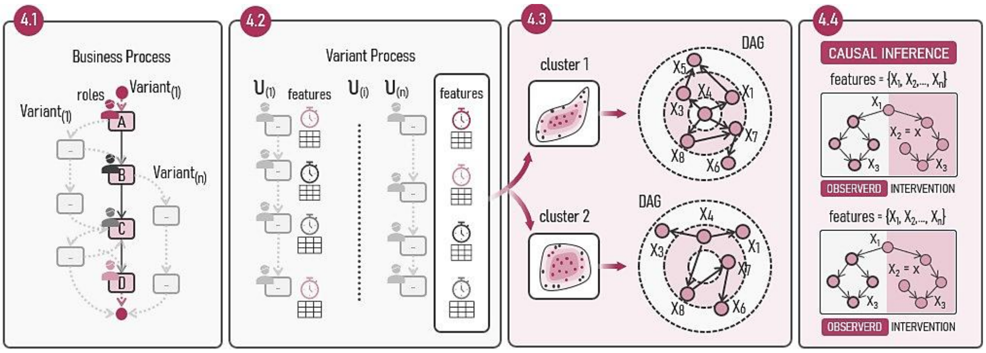

Fig. 2. Scheme of the proposed methodology for analyzing underlying causal relationships in temporally clustered deviations from a process variant.

or change when all data is combined, is avoided. In this way, precise causal relationships are identified, aligning with the specific strategic objectives of each process variant. This method reduces biases and interferences typical of general approaches such as those by Böhmer and Rinderle-Ma [13] and Janina et al. [14], who use general signatures and may encounter distortions when considering multiple variants simultaneously.

The following stages are closely related to addressing this problem. First, the individual process variants are identified, and then robust causal analysis is applied to each variant, ensuring precise and contextualized causal identification.

4.1 Event Log from Planning

The first stage of the methodology, illustrated in Figure 2, focuses on identifying the business process model using process mining [24]. For this purpose, event logs (L) derived from previously defined project plans are obtained. An event log is formally represented as a set of traces σ, where each trace σ_i consists of ordered sequences of activity-time pairs $\sigma_i = \{(a_1, t^i_{a_1}), \dots, (a_n, t^i_{a_n})\}$, following the notation presented in the Preliminaries section.

This strategy allows capturing the expected behavior of the process according to the original planning. Moreover, it enables the early detection of temporal deviations and the recognition of interactions among the roles involved in the process, as suggested by Pereira and Varajão [11]. This early detection is essential for understanding the causes of the deviations before they negatively affect the final outcomes. In this way, it contributes to a better understanding and management of the temporal and collaborative relationships among roles within the process flow.

Table 1. Event Log Extract

Case Id	Activity	Time-span	Role$_1$	...	Feature$_n$
case 1	A	10.3 ms	role.$_1$	...	feat.$_2$
case 1	B	45.2 ms	role.$_2$	...	feat.$_3$
case 1	C	62.5 ms	role.$_4$	...	feat.$_6$
case 2	A	72.4 ms	role.$_5$	...	feat.$_3$
...	...	...	...	...	...

In Table 1, a typical extract of the event log obtained from the project plans is shown. Each record presents the following essential attributes:

1. **Case-ID**: Unique identifier that distinguishes each process instance. *Examples* (ERP/CRM): C-2025-00451, OP-789231, TICKET-31415.
2. **Activity**: Activity performed at a point in the process. *Examples:* Request receipt, Data validation, Credit approval, Generate invoice, Close case.
3. **Timestamp(s):** Event timestamp(s) (*start and/or end*) to compute duration and waiting times between activities. *Example:* start 2025-06-15 09:34, end 10:12→duration 38 min.
4. **Role**: Role responsible for executing the activity (*function or profile*). *Examples:* Analyst, Supervisor, Back-office; (*optional*) individual resource u1234.
5. **Additional operational variables**: Attributes that contextualize the case or the event. *Examples:* priority (*High/Medium/Low*), channel (*Web/In-person*), product/service, customer segment, amount, number of items, location, SLA.

This structure facilitates clearly capturing the expected behavior of the process according to the initial planning. Moreover, it allows for the early identification of temporal deviations and reveals interaction patterns among roles. These elements provide a solid foundation for subsequent causal analysis, highlighting improvements over methods such as those described in [13] and [14], which tend to rely on more general representations.

4.2 Business Process Variant

The second stage of the methodology, in line with the definitions and notations established in the definition 2.1 (see Sec.2), focuses on extracting and characterizing operational variables from each process variant. Specifically, the execution times between consecutive activities within each process variant V_j, previously defined in the Preliminary section, are extracted. These times are transformed using the Modified Z-Score, formally defined as:

$$Z_m\left(\Delta t^i_{a_j a_{j+1}}\right) = \frac{0.6745\left(\Delta t^i_{a_j a_{j+1}} - \tilde{\Delta} t_{a_j a_{j+1}}\right)}{MAD\left(\Delta t_{a_j a_{j+1}}\right)}$$

where $\Delta t^i_{a_j a_{j+1}}$ is the time interval between consecutive activities for trace $\sigma_i, \tilde{\Delta} t_{a_j a_{j+1}}$ represents the median time interval in variant V_j, and MAD corresponds to the median absolute deviation. In this way, a temporal vector

$$Z_j = \left[Z_m\left(\Delta t_{a_1 a_2}\right), Z_m\left(\Delta t_{a_2 a_3}\right), \dots, Z_m\left(\Delta t_{a_{n-1} a_n}\right)\right].$$

is obtained, which will later be used as input for the clustering and causal graph discovery stages. Furthermore, this temporal vector forms the fundamental basis for clearly identifying and analyzing the specific temporal deviations of each process variant, thereby enabling a precise understanding of the underlying causal relationships.

4.3 Cluster of Temporal Deviations:

The third stage of the proposed methodology (see Figure 2) consists of applying the Gaussian Mixture Model (GMM) [25] to the temporal vectors normalized using the Modified Z-Score, previously described as Z_j. This vector serves as the input to the GMM, which is an unsupervised machine learning model, formally expressed as

$$p(Z_j) = \sum_{k=1}^{K} \pi_k \mathcal{N}(Z_j \mid \boldsymbol{\mu}_k, \Sigma_k),$$

where π_k is the weight of the k-th Gaussian component, $\boldsymbol{\mu}_k$ is the mean vector, and $\boldsymbol{\Sigma}_k$ is the covariance matrix associated with the component. The application of the model allows for the identification of clusters that group traces with similar patterns of temporal deviations.

These obtained clusters facilitate subsequent causal analysis on the associated operational variables. The identification of typical causal structures is illustrated in Figure 3, showing three basic configurations: Forks, Chains, and Colliders. Recognizing these causal patterns is crucial for interpreting the underlying dynamics in temporal deviations, which directly contributes to greater causal interpretability and the direction of the causal effect of interventions.

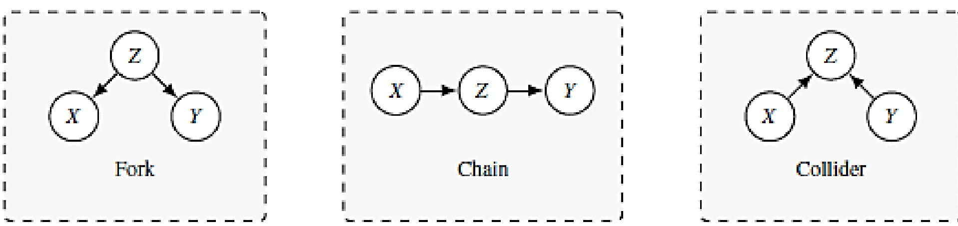

Fig. 3. Causal topologies (Fork, Chain, Collider) illustrating relationships among variables

To obtain the causal graphs (DAG), an iterative procedure based on techniques such as LiNGAM, PC, and GES is implemented, as described in Algorithm 1. This algorithm combines statistical tests for conditional independence with cycle elimination, thereby ensuring the generation of coherent causal graphs.

The resulting DAG offers a robust interpretation of how the operational variables causally impact the detected temporal deviations, facilitating the implementation of effective strategic interventions in process management

4.4 Interventionist Causal Design

Once the clusters of temporal deviations have been defined and the corresponding DAG has been obtained, the interventionist causal analysis is undertaken to determine the direction of influence among the variables and to implement targeted interventions. In this model, the treatment T is understood as the action applied to correct or improve the process, the outcome Y reflects the performance measured after the intervention, and the confounding variable Z groups the contextual factors that affect both.

The model is expressed using causal functions:

$$T := f_T(N_T), Y := f_Y(T, Z, N_Y),$$

where N_T and N_Y are independent noise terms. The intervention $\mathrm{do}(T = t)$ is applied to fix T at a specific value, which produces the distribution $P_{Y|\mathrm{do}(T=t)}$. By comparing this distribution with the observational one, the direct effect of T on Y is isolated while controlling for the influence of Z.

This interventionist approach confirms the causal direction and, unlike the methods of Qafari and Van der Aalst [20] and of Luo et al. [21], which relied on observational analyses without incorporating the perspective of intervention, enables the design of precise interventions. In this manner, improvement strategies can be established to optimize the flow of events within the business process.

Algorithm 1 Causal Discovery to Obtain the DAG (consensus)

Input: $D \in \mathbb{R}^{n \times p}$ (with p variables $\{X_1, \ldots, X_p\}$);
$B \in \mathbb{N}$ (number of bootstraps);
$\tau \in [0, 1]$ (inclusion threshold).
Output: $\mathcal{G}^* = (V, E^*)$ with $V = \{X_1, \ldots, X_p\}$.

Definitions: For each $b = 1, \ldots, B$ and $X_i, X_j \in V$:

$$\delta_{ij}^{(b)} = \begin{cases} 1, & \text{if } \exists m \in \{\text{LiNGAM, PC, GES}\} : \; X_i \to X_j \text{ in } D^{(b)}, \\ 0, & \text{otherwise.} \end{cases}$$

Let $v_{ij} = \sum_{b=1}^{B} \delta_{ij}^{(b)}$, $f_{ij} = \frac{v_{ij}}{B}$, and $E_{\text{pre}} = \{(i, j) \mid f_{ij} \geq \tau\}$.
d-sep(X_i, X_j, Z) returns `true` if X_i and X_j are d-separated by Z in $\mathcal{G}$, else `false`.

for $b \leftarrow 1$ *to* B **do**
  $D^{(b)} \leftarrow$ bootstrap sample of D; **foreach** $(i, j) \in V \times V$ **do**
    if $\exists m \in \{\text{LiNGAM, PC, GES}\}$ *with* $X_i \to X_j$ *in* $D^{(b)}$ **then**
      $\delta_{ij}^{(b)} \leftarrow 1$ /* *Causal edge detected in current bootstrap sample* */
    else
      $\delta_{ij}^{(b)} \leftarrow 0$ /* *No causal edge detected in current bootstrap sample* */
    $v_{ij} \leftarrow v_{ij} + \delta_{ij}^{(b)}$

foreach $(i, j) \in V \times V$ **do**
  $f_{ij} \leftarrow \frac{v_{ij}}{B}$ /* *Calculate frequency of edge occurrence* */

$E_{\text{pre}} \leftarrow \{(i, j) \mid f_{ij} \geq \tau\}$; $\mathcal{G}_{\text{pre}} \leftarrow (V, E_{\text{pre}})$ **while** $\mathcal{G}_{\text{pre}}$ *contains a cycle* C **do**
  $E' \leftarrow \{(i, j) \in C \mid \text{d-sep}(X_i, X_j, Z) = \texttt{true}\}$; **if** $E' \neq \emptyset$ **then**
    $(i^*, j^*) \leftarrow \arg\min_{(i,j)\in E'} v_{ij}$ /* *Lowest support edge selected* */; Remove (i^*, j^*) from E_{pre} /* *Edge removed to break cycle* */; Update $\mathcal{G}_{\text{pre}} \leftarrow (V, E_{\text{pre}})$ /* *Graph updated* */
  else
    break /* *No removable edge found: process terminated* */

return $\mathcal{G}^* \leftarrow \mathcal{G}_{\text{pre}}$

5 Results

This section presents the findings obtained by applying the methodology described in Section.4 to an event log documenting the planning and development of technological requirements at a payment services company. A total of 562 instances were evaluated, allowing for the identification of patterns in temporal deviations and in the operational structure of the process.

5.1 Dataset Description

The analysis was conducted on an event log that records the sequence of activities, start and end times, and other operational attributes for each planning instance. Each instance documents a complete process, capturing both the planning and execution phases. Table 2 summarizes the main characteristics of the dataset.

Table 2. Dataset Characteristics

Characteristic	Value
Planning Instances	562
Number of Unique Activities	8
Average Events per Planning	10
Registered Operational Attributes	12
Time Period	2018ţ 2020
Source	Event Log

5.2 Principal Findings

The process model quantifies the duration of key activities and detects critical paths (see Figure 4). Notable differences were observed in tasks such as User Evaluation Clarification (averaging 34.9 days) and Production Testing Evaluation (47.4 days), both of which have a significant impact on the workflow. Additionally, Quotation Approval reaches 33.4 days, while Functional Definition (23.7 days) and Planning (13.7 days) also stand out due to their complexity.

On the other hand, “Technical Evaluation” records 11 days, Quotation Generation 7.2 days, and Completeness Review 5 days, reflecting relatively shorter durations. These figures highlight the heterogeneity of processing times and help identify critical paths within the process.

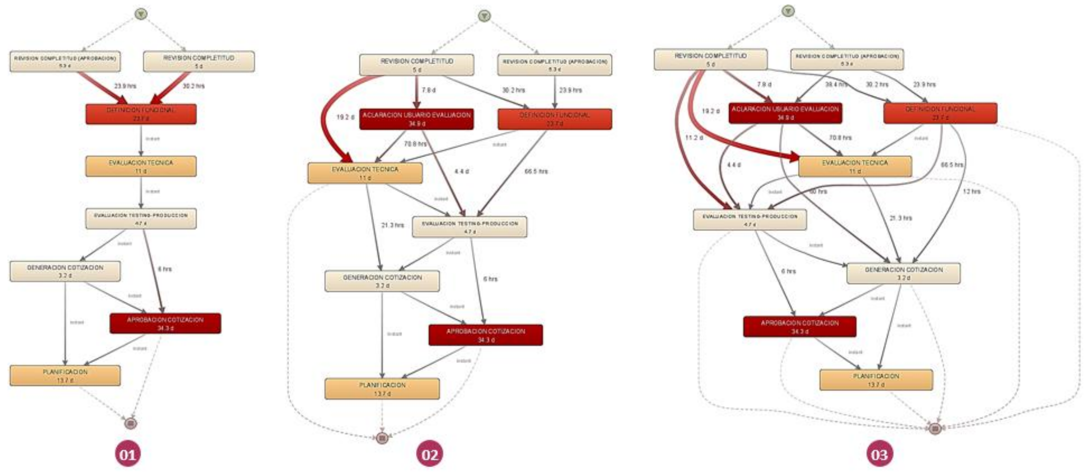

Fig. 4. Three representations of the same process with different relevance filters: (**1**) activities related to Quotation Approval are highlighted, (**2**) flow variants that modify the sequence of activities are shown, and (**3**) a bottom-up view focused on execution.

5.3 Temporal Deviations Clustering

To study the temporal deviations within the variant, GMM and PCA were applied to the execution times. Figure 5 shows two main classes (class = 0 and class = 1), with 348 and 168 instances respectively, along with 46 cases of overlap. This overlap exhibits an entropy of $H(X) = -\sum_i p(x_i) \log p(x_i) = 0.82$, indicating a moderate ambiguity in class separation. This clustering facilitates the identification of similar deviation patterns; for instance, class=1 includes traces with greater delays in User Evaluation Clarification and Quotation Approval, suggesting a significant impact on overall planning.

5.4 Interventionist Causal Analysis

In the subgroup of *class = 1* (168 *planning instances with similar patterns*), a causal analysis focused on the activity *Clarification User Evaluation* was applied. For this purpose, the following operational variables were identified (*see* Table 3):

Table 3. Variables in "Clarification User Evaluation".

Variable	**Description**	**Role**
scheduled_hours	Scheduled hours.	Treatment (*T*)
num_requirements	Requirements to clarify.	Outcome (*Y*)
complexity_level	Complexity level (1 to 3).	Confounder (*Z*)

The causal model is defined as:

$$T := f_T(N_T)$$
$$Y := f_Y(T, Z, N_Y)$$

where T represents the scheduled hours and Y the number of requirements. N_T and N_Y are independent noise terms, while Z groups confounding factors such as the project's complexity and the number of services involved.

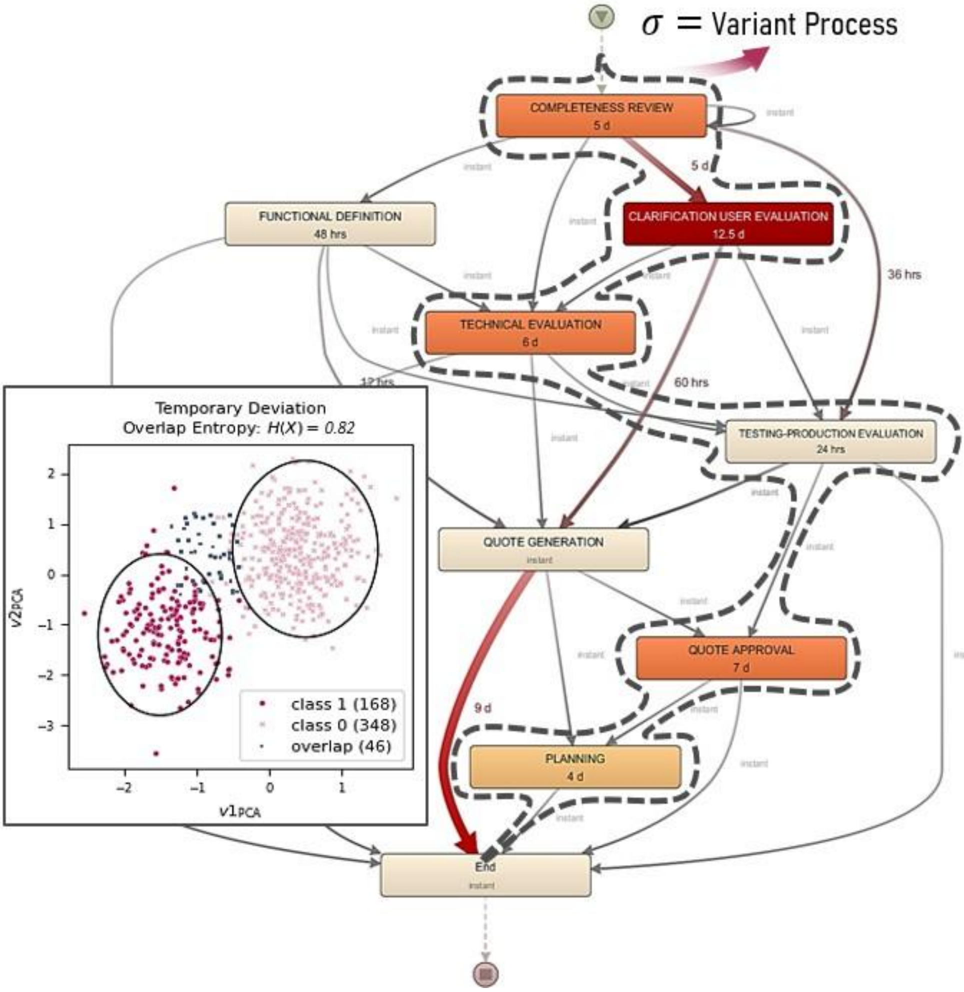

Fig. 5. Process variant with segmented activities and temporal deviations clustering. Two classes (class=0 and class=1) are observed, with 46 overlapping cases and an entropy of H(X) = 0.82.

To illustrate the analysis, the intervention $\mathrm{do}(T = 2.5)$ was applied, fixing T at 2.5 hours. This allowed us to obtain the distribution $P_{Y|\mathrm{do}(T=2.5)}$ and compare it with the observational distribution, thereby isolating the effect of T on Y. The average causal effect (ATE) was calculated as:

$$\mathrm{ATE}(t, t') = \mathbb{E}[Y \mid do(T = t)] - \mathbb{E}[Y \mid do(T = t')]$$

yielding a value of -0.19 per additional hour. For an increase of 12 hours (from 2.5 to 14.5), the ATE was -2.35. The causal structure (see Figure 6) was derived using lingam [28,30], as well as the PC and GES algorithms [29] (see algorithm 1). As shown in Figure 6, scheduled hours has a direct effect on num requirements, while complexity level acts as a confounding variable.

6 Discussion

The analysis showed that the activities Clarification User Evaluation (12.5 days) and Testing Production Evaluation (24 days) exhibited prolonged durations (see Figure 5). Sequences were also detected in which minor delays accumulate and create bottlenecks. These results make it possible to locate critical points in the process and guide targeted interventions to improve performance (see RQ.2).

The findings are consistent with research that prioritizes attention to stages with greater delays. Böhmer and Rinderle [13] use temporal signatures to detect anomalies early, whereas

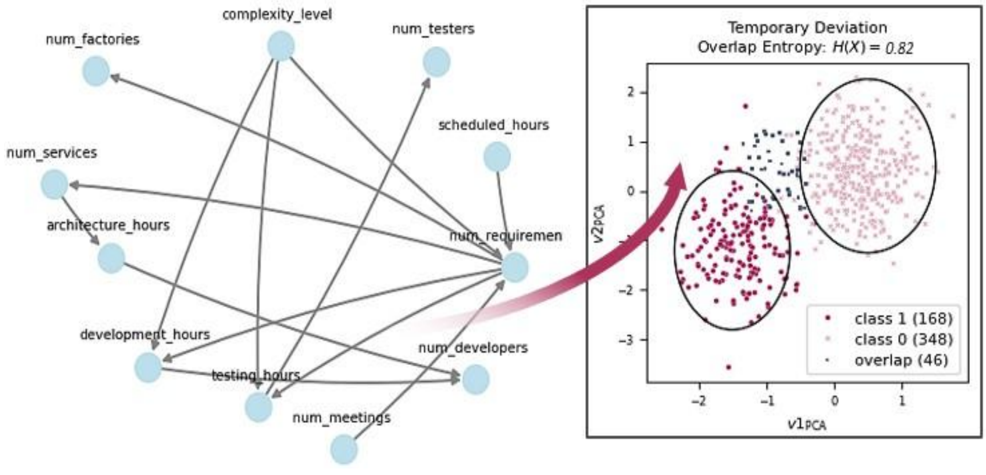

Fig. 6. Causal graph depicting operational variables within the Clarification User Evaluation activity, with causal relationships identified using causal discovery techniques.

Janina et al. [14] incorporate detailed signatures to identify deviations between consecutive activities. Although these approaches present limitations in lengthy processes, they reinforce the need to manage critical stages effectively (*see* RQ.2).

The use of a real dataset (562 *planning instances*) and the focus on specific activities strengthen the validity of the observations. Nevertheless, the limited time window and reliance on a single dataset constrain generalization. Future studies should consider different organizational contexts and extend the observation period to assess the stability and applicability of the results (*see* RQ.1).

It is also pertinent to examine the influence of organizational factors, such as resource allocation and the adoption of automation technologies on reducing temporal variations. This would allow a deeper understanding of how specific interventions improve process efficiency (*see* RQ.3).

In summary, the precise identification of critical activities and the analysis of problematic sequences provide a clear basis for targeted interventions. Their implementation can reduce execution times and improve operational efficiency, contributing to the optimization of overall process management (*see* RQ.3).

7 Conclusions

This work integrated process mining and causal machine learning to identify and explain temporal deviations in enterprise workflows. The methodology combines causal discovery techniques with the analysis of event logs to improve the interpretability of variations in execution times.

The results indicate that certain activities are associated with delays and that their impact can be assessed through causal interventions. The estimation of the average causal effect quantified the effect of variables such as scheduled hours and complexity level on process duration.

Although the approach is applicable in different settings, generalizing the findings requires testing it across diverse organizational configurations and expanding the dataset. Future work can explore the role of resource availability and automation in reducing deviations.

In summary, the incorporation of causal models into process mining provides a useful framework for optimizing operational management. Understanding cause-and-effect relationships facilitates the design of more precise interventions, leading to reduced execution times and greater efficiency in process planning.

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