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Let the record show: a structured approach to process analytics in judicial contexts

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Abstract
Process mining and other forms of event data analytics have shown to be valuable tools for supporting the management and execution of business processes. For this, process recordings in the form of event logs are required. Digitalization efforts have led to an increased availability of event data for many previously paper-based processes. This has also inspired the extension of process analytics beyond classical business processes. One example of this is judicial processes, which are not necessarily bound by typical business constraints, but nonetheless face issues related to, e.g., increasing efficiency or improving resource allocation. Thus, this paper proposes a structured approach that combines domain expert knowledge with data-driven analysis to explore the usefulness of process analytics for judicial processes. Using an exemplary use case from a German social court, we show how event logs can be extracted from digitalized court files and, using our approach, identify bottlenecks. Using this approach, we are able to derive statistically grounded and expert validated bottlenecks as well as four actionable insights for reducing case durations. Thereby, we show that process analytics is a promising tool for facilitating the optimization of judicial processes.

Keywords Process mining, Workflow inefficiencies, Judicial processes, Use case

Introduction

With their process-first perspective, process mining and other forms of process analytics have shown to be valuable tools in various applications involving business processes, e.g., to identify bottlenecks in processes, detect deviations from expected workflows, and support data-driven process optimization (Reinkemeyer 2020). Typically, process analytics relies on event logs, which are recordings of business processes extracted from business information systems. Due to the advancing of digitalization, an increasing number of processes are supported by information systems. As a result, more process-related event data is becoming available for analysis (Unger et al. 2021). While on the one hand, this enables gaining a deeper perspective on business processes, on the other hand, it has also inspired extending the scope of process analytics beyond typical business settings (Lepsien et al. 2022; Fonger et al. 2023; Brzychczy et al. 2025).

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Process mining is increasingly being recognized as a valuable tool in the legal domain, offering data-driven insights into the workflows of judicial and administrative processes. Legal systems operate through highly structured yet often inefficient procedures, where case handling, documentation, and decision-making involve multiple actors and dependencies (Campi et al. 2025). Process mining has the potential to improve transparency, identify procedural inefficiencies, and optimize resource allocation within legal institutions. While its applications have been explored in areas such as compliance monitoring, contract management, and legislative analysis (Vercosa et al. 2024), this paper focuses on the judiciary, specifically court proceedings, as an application domain for process analytics. This is because court proceedings involve complex, yet rule-based workflows with high societal impact, where delays and inefficiencies directly affect access to justice and case outcomes.

In recent years, courts are starting the transition to electronic case management, which enables the extraction of structured event logs (Castelliano et al. 2023). With digital case files becoming mandatory in many countries in the near future (e.g., starting January 2027 in all of Germany), an even larger availability of event data can be expected. Judicial processes share structural characteristics with business processes (Unger et al. 2021) (as will be discussed in detail in Sect. 2.1). This suggests that exploring the application of process analytics to judicial processes could provide a valuable set of tools for this domain while simultaneously extending the scope of process analytics beyond traditional business processes.

Consequently, the goal of this paper is to investigate the applicability of process analytics to judicial processes and other complex domains. For this, we present a statistical, strongly domain-expert-driven approach and evaluate it through a case study on the handling of lawsuits in a German social court. In the case study, we extracted an event log, analyzed it with an approach combining data-driven findings and expert knowledge, and generated actionable insights for process improvement. Besides demonstrating the applicability and usefulness of process analytics for judicial processes, we also give insights how to successfully conduct an analysis in this domain. Additionally, the real-world event log extracted from the court data along with descriptions of activities is provided for future research.

This paper is based on a conference paper (Aleknonyte-Resch et al. 2025b), which was revised and extended. Particularly, the main extensions are:

- A detailed characterization of judicial processes and their relationship to business processes, including a discussion of the unique properties that influence how process analytics can be applied and how it can be ensured that insights are adopted.
- An extended and more abstract presentation of our exploratory analysis approach, accompanied by additional reasoning regarding its design and relation to existing literature, making it less domain-specific and thus transferable to processes in other domains.
- An extension of the analytical framework by incorporating descriptive statistics in the beginning, testing for data normality prior to correlation analysis, and applying variance inflation factors (VIF) to identify which variables should be included in the regression analysis.
- A reanalysis of the social court use case using the revised, more structured approach, including how domain expert knowledge informed specific analytical steps and

jointly reinterpreting the results with domain experts, thereby identifying an additional actionable insight.
- An update of the dataset, which now includes (1) comprehensive explanations of all activity labels, written with domain experts, and (2) structured information about the organizational units that participate in each activity (and their mode of participation).

The remainder of the paper is structured as follows. Section 2 provides the background, including the judicial peculiarities of the use case and relevant literature. Section 3 details our process analytics approach tailored to the requirements of the judicial domain. Section 4 describes the case study context, the dataset, and the instantiation of the analysis approach for the case study. Section 5 presents the corresponding analysis results. Finally, Sect. 6 summarizes our findings, discusses limitations and lessons learned from the case study, and presents directions for future research.

Background

In this section, we establish the theoretical and contextual background of our analysis approach. First, we contrast business and judicial processes in Sect. 2.1 and discuss the unique properties of judicial processes that need to be considered when applying process analytics techniques – that were originally designed for business processes – to them. Then, Sect. 2.2 reviews related work on judicial process mining and differentiates it from our approach.

Business and judicial processes

We characterize and compare business and judicial processes on three levels, as summarized in Table 1. First, Sect. 2.1.1 examines structural similarities and differences, showing sufficient similarity between the two types of process that process analytics techniques are generally applicable to judicial processes but may need to be adapted to their specific properties. Second, Sect. 2.1.2 discusses the respective notions of process quality and the unique quality constraints of judicial processes. Third, Sect. 2.1.3 concerns the conditions governing process improvement initiatives in the judiciary and their influence on analysis design.

Structural similarities and differences

In this paper, we focus on the handling of lawsuits from the perspective of the court. While process mining techniques were originally designed to analyze business processes, the fundamental structure of lawsuits is sufficiently similar to business processes that they are also generally compatible with process-centric analysis (Unger et al. 2021; Caponecchia et al. 2025). Like business processes, lawsuits can be understood as discrete cases[1] with unique identifiers (case IDs) consisting of sequences of distinct procedural steps (activities) recorded with specific timestamps (Unger et al. 2021). Accordingly, the steps represent transitions between different states of the process, e.g., when a request for evidence has been sent and an answer is awaited.

Beyond this basic mapping, judicial processes exhibit the same workflow patterns as business processes:

[1] That is: *court cases*

Table 1 Comparison of the shared and specific properties of business and judicial processes

Aspect	Commonalities	Business Process	Judicial Process
Structural Aspects (Sect. 2.1.1)			
Basic Elements	Distinct steps between different states	Business activities	Procedural steps
Control Flow	Sequences, Choices, Parallelism, Repeating Patterns	More structured, often choreographies between resources/departments	Central orchestration by judge according to procedural law
Quality Dimensions (Sect. 2.1.2)			
Primary Goal	Coordinated handling and completion of cases	Business-specific, e.g., produce item, handle claim	Issue fair and just (substantive) judgement
Flexibility	Standardization possible for routine sub-processes	Low–medium variability, higher standardization	High variability, individualized treatment mandatory for each case
Quality	Higher quality generally increases time/cost	Tradeoffs often acceptable (e.g., quality–cost)	Highest quality standards must be upheld in all cases
Time	Risk of over-optimization	Importance varies per use case (continous supply chain vs. insurance)	Primary factor for perceived justice, principle of reasonable duration
Cost	Economically rational improvement choice	Essential, hard constraint in for-profit businesses	Secondary concern
Analysis Objective	Improve process quality	Varying focus, tradeoffs admissible	Optimze duration without compromising justice
Practical Challenges (Sect. 2.1.3)			
Intervention Options	Redesign process, support specific steps	Higher autonomy in process design and execution	Restricted by procedural laws and sovereignty
Adoption	Facilitated by perceived usefulness and trust	Higher leverage, e.g., contractual enforcement	Enforceability limited by judicial independence

- **Choices:** Lawsuits involve numerous decision points where different paths can be chosen depending on the context and properties of the case.
- **Concurrency:** Lawsuits often include parallelism, e.g., a court simultaneously requests a report from an expert witness and missing files from the plaintiff.
- **Repeating Patterns:** Lawsuits contain loops (e.g., iterative requests for clarification of a written statement) and standardized sub-routines (e.g., issuing and sending directives) that can reappear at various stages of the case.

Intuitively, this structural alignment suggests that the benefits of process mining, which has been applied successfully to a wide range of real-world business processes (Reinkemeyer 2020), could extend to judicial processes. By harnessing structured event data for analysis, courts can identify potential causes of delays, visualize variations, and systematically detect bottlenecks (Pernici et al. 2023; Caponecchia et al. 2024, 2025).

However, judicial processes also have unique characteristics distinguishing them from business processes. First, because judicial processes are fairly complex and require individualized treatment for each specific case, event logs will typically contain many heterogeneous process variants (Caponecchia et al. 2025). This poses a challenge: Process mining techniques work best with structured processes (Diamantini et al. 2016), and a lack of *global conclusiveness*, i.e., when a process is not structured enough that specific, significant happy paths or structural patterns show frequently across its instances, can substantially impact the usefulness of process mining results (Lu and Fahland 2017). Second, whereas business processes often consist of choreographed interactions between different resources or departments (e.g., an order progresses from sales to the warehouse, then to shipping, and so on) (Dumas et al. 2018), control in judicial

processes is more centralized, with (almost) all decisions being orchestrated on the final account of the judge. These distinctions influence both the goals and methods of process-centric analysis, which we will discuss in the following.

Quality goals of business and judicial processes

Generally, Business Process Management (BPM) aims to *improve* processes (Dumas et al. 2018). The desired outcome of a process is called its primary goal (Adamo et al. 2018), and the instrumental purpose of the process is to reach this primary goal by handling and completing cases in a coordinated manner. When analyzing processes for improvement, the general notion of *improvement* is specified through *quality goals*, which assess *how well* a process achieves its primary goal (Adamo et al. 2018). Notable similarities between business and judicial processes include that both aim to add value to their organization (Dumas et al. 2018), both are concerned with supporting the work of people inside these organizations, and most importantly, both often face identical questions, e.g.: *How should resources (machines, workers, judges, etc.) be allocated? How can we improve lead times? What are the possible causes of delays in the process? Are there bottlenecks?*

Overall however, there are significant differences between their primary and quality goals. Common overarching goals of business processes are high organizational performance (Heidari and Loucopoulos 2014) or generating a return on investment (Messer 1999). Their typical quality goals accordingly include performance, efficiency, reliability, availability, security, and usability (Heidari and Loucopoulos 2014; Adamo et al. 2018). In contrast, judicial processes generally aim to resolve conflicts in a *fair* and *just* manner (Sourdin and Burstyner 2014), which implies a different notion of process quality. Here, commonly discussed quality goals include independence, accessibility, efficiency, effectiveness, and transparency (Cross and Donelson 2010; Sourdin and Burstyner 2014; Grimmelikhuijsen and Klijn 2015).

Multiple process quality frameworks exist, describing process quality in terms of various quality dimensions. One of the most important and widely used generalized process quality frameworks is called the "Devil's Quadrangle", consisting of four distinct goal dimensions for process redesign, i.e., *time*, *cost*, *quality*, and *flexibility* (Dumas et al. 2018). While a redesigned process would ideally improve all four dimensions simultaneously, real-world BPM typically needs to balance tradeoffs between these dimensions (Dumas et al. 2018). Which quality dimensions and specific measures are appropriate depends on the properties and goals of the specific use case (Messer 1999; Heidari and Loucopoulos 2014).

Figure 1 visualizes the quadrangle and compares the ranges of possible redesign options in the business (Fig. 1a) and judicial (Fig. 1b) domains. For business processes, all quality dimensions are admissible for tradeoffs in principle. This includes *quality*, which might for instance be reduced (by removing quality control steps) to reduce *cost* (Dumas et al. 2018). However, removing quality control steps does not automatically reduce cost: cost savings arise only if the freed resources can be reduced or reallocated to other tasks. Another example is the intentional reduction of *flexibility* through standardization to reduce *cost* and improve throughput *time*. In contrast, judicial processes operate within a substantially constrained space of admissible redesign options. Here, *quality* (substantive justice, i.e., ensuring fair and just judgments) is the primary quality

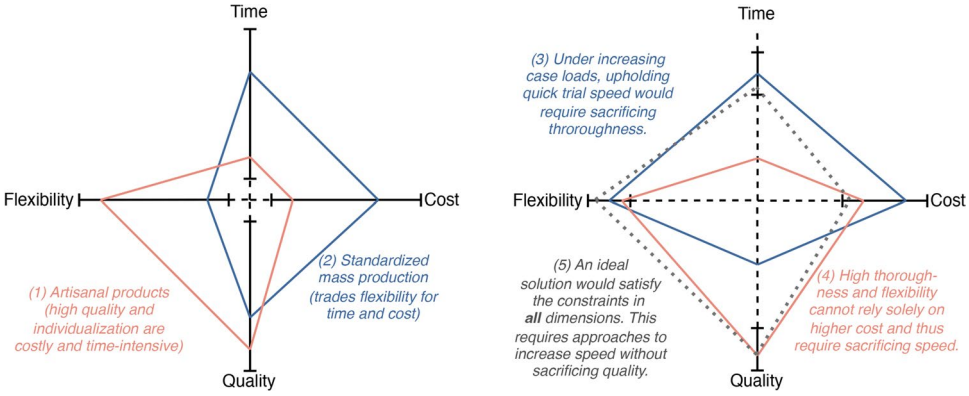

Fig. 1 Devil's quadrangle (Dumas et al. 2018), encompassing four interdependent quality dimensions influencing each other during process redesign. The space of possible redesign options and example processes are shown for business (Fig. 1a) and judicial (Fig. 1b) processes respectively

goal that must always be upheld and cannot be traded off against. The *quality* of judicial processes is closely linked to ensuring that every case receives appropriate, highly individualized treatment (*flexibility*) (Caponecchia et al. 2024). While *cost* is generally less important than in for-profit businesses, courts might also face pressures (e.g., governmental) to reduce cost, and generally, cost is a fairly inflexible parameter for redesign as it is mostly fixed according to (externally set) public budgets. Thus, as *quality*, *flexibility*, and *cost* requirements are (quasi) fixed in the judiciary, and given the increasing complexity of legal issues, the necessary thoroughness of judicial investigation is reflected in considerable increases in case durations (*time*) (Meller-Hannich et al. 2023; Caponecchia et al. 2024). However, *time* is connected to *quality* in a complex manner:

- **Quality Requirement:** High judgment quality requires thorough and thus time-intensive investigation and trials (Caponecchia et al. 2024)
- **Quality Risk:** Excessive optimization of case duration risks compromising the thoroughness and therefore quality of judgments (Caponecchia et al. 2024)
- **Quality Benefit:** Case duration is a primary factor influencing whether the judicial system is perceived as fair and just (Sourdin and Burstyner 2014).

Navigating this tradeoff should follow the *principle of reasonable duration* (Caponecchia et al. 2025) which mandates lawsuits to be as quick as possible while taking the complexity of the specific case into account (Sourdin and Burstyner 2014). Accordingly, applications of BPM in the judiciary are mostly limited to improving the *time* dimension and thus typically focus on increasing efficiency. For instance, automating standardized activities through digital technologies (Cross and Donelson 2010) might free resources to be allocated elsewhere. Another improvement option is the reduction of delays. As perceived fairness is maintained as long as delays to a lawsuit appear reasonable given the complexity of the case (Sourdin and Burstyner 2014), analysis requires careful distinction between reasonable delays, e.g., thorough investigation, and avoidable delays such as administrative friction. Whether a delay is reasonable can often not be decided from data alone but requires considering domain expertise (Bianchini et al. 2024).

Constraints for process improvement

The final level of comparison concerns the practical application of process analytics in the form of project-level considerations and constraints that influence how interventions are prepared and implemented. While the structural (Sect. 2.1.1) and goal-focused (Sect. 2.1.2) aspects primarily concern whether analysis of judicial processes with BPM methods is feasible and how it can sensibly be conducted, the analysis of judicial processes needs to consider two unique distinctions, i.e., hard procedural requirements defined by law and constitutionally protected judicial independence.

For business processes, process improvement often involves the redesign of workflows (Dumas et al. 2018). Typically, businesses have a high degree of autonomy over the design and execution of their processes, and they can thus explore a wide range of redesign options. While ensuring the implementation and adoption of suggested process improvements is already a considerable challenge with business processes (Tentina et al. 2025), management can ultimately enforce adoption by managerial decree using contractual leverage.

In contrast, both aspects are subject to hard constraints in the judiciary. First, many steps in a lawsuit are mandated by procedural law and cannot be removed or altered considerably. Thus, for parts of the process that cannot be restructured, improvement options are constrained to increasing the efficiency of the predefined steps, e.g., by implementing information systems to support or automate them (Cross and Donelson 2010). While analysis might also yield insights about how the structure of legally mandated parts of the procedure could be improved, these insights cannot be leveraged directly. Still, they might be relevant for policy discussion and can inform future revisions of procedural law, as exemplified by the introduction of (mandatory) digital case management in many countries in recent years (Castelliano et al. 2023). Second, judicial independence, which constitutionally guarantees judges broad autonomy over how they handle lawsuits, sets a hard limit on the leverage that improvements can be enforced with.[2] Due to this, even when an analysis produces useful and immediately actionable insights, judges cannot be *forced* to adopt changes. Conversely, analysts can generally only *suggest* possible improvements and offer, e.g., automated solutions for repetitive manual tasks, but each judge autonomously decides whether to adopt these suggestions.

A central determining factor for adoption is trust, i.e., the belief that a system (for instance automated steps of a process) works as expected (Mcknight et al. 2011; Müller et al. 2024). Adoption can be hindered if trust is missing (Dhungel and Beute 2024; Müller et al. 2024). Moreover, trust typically develops dynamically over time (Müller et al. 2024). Important ways to gain initial trust in process mining results are reliance on personal and colleagues' experience (Tentina et al. 2025). Therefore, to build such experience, judges (and possibly other court staff) that actually execute the processes, or trusted representatives, must be actively integrated into the development of analyses. This is closely linked to the explainability of analysis techniques and results, which is another factor influencing the acceptance and adoption of BPM initiatives in the judiciary (Caponecchia et al. 2025).

[2] Even changes in procedural law are limited in scope and can only be enforced to a certain degree.

Related analyses and approaches

To complete the background, we complement the conceptual considerations with an overview of related applications and approaches. First, Sect. 2.2.1 provides an overview how process analytics has been used specifically in the judicial domain. Second, considering the unique role of time and efficiency as the primary lever for process improvement in the judiciary (see Sect. 2.1.2), Sect. 2.2.2 provides a general overview of process-centric techniques to improve process efficiency.

Process analytics in the judiciary

Existing work on judicial process analytics primarily consists of case studies examining civil and labor proceedings, with a strong focus on the jurisdictions of Italy and Brazil. Applied descriptively, process mining and other data-driven techniques are for instance used to assess the impact of digitalization on court efficacy (Castelliano et al. 2023) and to analyze the evolution of processes over time (Caponecchia et al. 2024). Others use process mining as part of predictive or prescriptive analysis, for instance to identify activities significantly impacting process duration (Unger et al. 2021; Pernici et al. 2023; Caponecchia et al. 2024), to detect sources of process delays (Pernici et al. 2024; Campi et al. 2025), to engineer features for machine learning (Vercosa et al. 2024), to predict the remaining duration of ongoing cases, e.g., for operational support (Pernici et al. 2024; Campi et al. 2025), and to communicate analysis results to stakeholders (Unger et al. 2021). As expected, due to the domain-specific constraints (see Sec. 2.1), the majority of existing work examines quality in terms of *time*, primarily measuring performance through case duration (e.g., Unger et al. 2021; Vercosa et al. 2024). While the need for close expert integration in addition to data-driven analysis in the judiciary is generally acknowledged in the literature (Bianchini et al. 2024, cf. Sect. 2.1.3), existing work has mostly focused on the data perspective, integrating expert knowledge only selectively and mostly by proxy. Consequently, the field could benefit from analysis approaches that integrate domain experts in a comprehensive and systematic manner. Additionally, to the best of our knowledge, no existing case study applies process mining in the specific jurisdictional context of Germany or in social courts, which typically operate differently than civil or labor courts (see Sect. 4.1). Thus, as we will consider a use case from a German social court to demonstrate our approach, we also extend the existing body of practical case study knowledge geographically (by contributing experiences from German jurisdiction) as well as topically (by considering the distinct mode of social, as opposed to civil, proceedings).

Bottleneck analysis

Identifying process inefficiencies or performance anomalies and their causes, which are also called bottlenecks (Ibidunmoye et al. 2015), was a common goal in papers analyzing judicial processes. Various techniques exist to detect bottlenecks, for instance using statistics or machine learning (Ibidunmoye et al. 2015). With its process-first perspective, process mining has been shown to be a viable method for bottleneck analysis. To this end, Bemthuis et al. (2021) review approaches to detect and predict bottlenecks as well as recommending improvements using process mining. Based on this, Piest et al. (2023) present a method for handling bottlenecks using process mining. In most existing approaches (see Bemthuis et al. 2021; Piest et al. 2023), process mining is generally used

as a supportive tool, e.g., discovered process models annotated with throughput times are inspected manually to identify bottlenecks (Bemthuis et al. 2021; Unger et al. 2021). Techniques using process mining for the automated detection of bottlenecks primarily exist for specific applications. For instance, Fang and Yu (2024) discover a process model of a manufacturing process, which is then used for simulation-based bottleneck identification. Overall, explicit algorithmic techniques for bottleneck analysis have rarely been applied to judicial use cases. Likely, this is because the highly variable structure of lawsuits (see Sect. 2.1.1) poses significant challenges for purely data-driven process mining techniques, requiring their combination with additional (e.g., statistical) techniques and knowledge-driven analysis (Bianchini et al. 2024; Caponecchia et al. 2025).

A systematic approach to judicial process analytics

In this section, we present a systematic approach for judicial process analytics, which is designed to specify general process mining guidelines to ensure that the unique requirements of the domain are met as outlined in Sect. 3.1. Then, Sect. 3.2 describes the data processing steps, Sect. 3.3 details the mining and analysis procedures, and Sect. 3.4 outlines the approach for the evaluation of results.

Purpose and overall structure of the approach

We designed our analysis approach aligned to the widely-used PM^2 methodology, which divides process mining projects into six subsequent (iterative) phases (van Eck et al. 2015): (1) *planning* the scope (analyzed process) and research questions, (2) *extracting* relevant event data from information systems, (3) *data processing* to prepare and enrich this event data, (4) *mining and analysis* of the data, (5) *evaluating* the results with stakeholders and deriving improvement ideas, and (6) implementing them for *process improvement and support*.

PM^2 is designed for a broad range of contexts and analysis goals. Thus, it is intentionally generic, and in concrete projects, each abstract phase must be specified for the given use case. The gap between the abstract PM^2 methodology and the concrete needs of each particular use case is commonly bridged by analysis approaches operating at an intermediate level of abstraction, i.e., approaches for use cases *of some type* with *specific properties*. For instance, Föhr et al. (2025) specify PM^2 for business auditing, or Miri et al. (2025) for the extraction of object-centric event data. Accordingly, our approach is tailored to the requirements of the judicial domain as established in Sect. 2 – particularly, it is designed to:

- efficiently handle high structural variability (Sect. 2.1.1) by integrating process mining with other analytical techniques (Sect. 2.2.2),
- ensure that its improvements are admissible given the quality constraints, and thus focus on improving *time* (Sect. 2.2.1) without reducing *quality* (Sect. 2.1.2),
- and closely integrate stakeholder to ensure that results are useful (Sect. 2.2.1) and trusted sufficiently to facilitate autonomous adoption (Sect. 2.1.3).

Figure 2 gives an overview of our analysis approach that can be understood to specify phases 3–5 of PM^2. As discussed above, while the approach primarily aims to improve the *time* dimension, analysis cannot follow a single-objective optimization approach focusing on case duration. Rather, it must distinguish between reasonable and

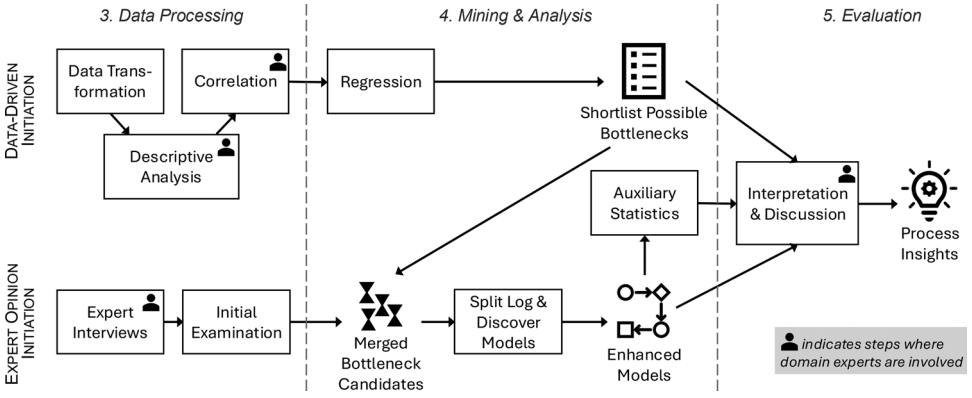

Fig. 2 Analysis approach systematically combining expert opinions and statistical analysis, aligned to the phases of the PM^2 methodology

unreasonable delays (Sourdin and Burstyner 2014) to produce useful results, and this requires considering the context of activities (Ahmadi et al. 2026, Franzoi et al. 2025). As process analysts are typically unfamiliar with the analyzed processes, they must integrate domain expert knowledge (van Eck et al. 2015; Beerepoot et al. 2023; Bianchini et al. 2024), which can be done at different points during analysis (Dixit et al. 2017). For instance, De Koninck et al. (2017) integrate expert knowledge early to seed clusters for trace clustering, and Dixit et al. (2017) incorporate expert knowledge in a post-processing step after discovery for model enhancement.

Including expert knowledge early *and* continuously helps guiding analysis and ensuring that results are useful for stakeholders (van Eck et al. 2015; Koschmider et al. 2024). Additionally, integrating domain experts in multiple steps of the analysis facilitates adoption because it builds personal and collegial experience, which has been shown to be an important way of building trust (Tentina et al. 2025). Thus, the analysis approach employs a two-fold initiation procedure that combines (A) a data-driven statistical analysis with (B) domain expert knowledge. Because these two branches cover two complementary perspectives, this combination ensures a broad identification of potentially relevant factors (Alonso et al. 2012). Additionally, the two-fold initiation helps to identify and reduce bias by acting as a triangulation mechanism – while data-based analysis and expert opinion are both subject to their own inherent biases (Mannhardt 2022), combining the two *differently* biased perspectives informs critical reflection: candidates resulting from both initiation branches are less likely to be the (misleading) result of a *specific* bias than candidates that only appear promising from a single perspective. In the following, we explain the steps of the analysis approach and discuss corresponding analysis activities that are appropriate given the characteristic requirements of the judicial context (and, by extension, of similar contexts characterized by high decision autonomy and non-negotiable quality constraints, as will be discussed in Sect. 6). Table 2 summarizes the statistical techniques used for analysis. As our approach focuses on phases 3–5 of PM^2, it presupposes that a relevant process was already identified (phase 1) and related event data extracted (phase 2).

Data processing

The aim of the *Data Processing* phase is to identify candidate factors for further investigation in the subsequent analysis phases, which is done in two separate branches. The

Table 2 Overview of the statistical techniques used

Step and Statistical Approach	Purpose	Implementation
Data Processing (Sect. 3.2)		
Descriptive Analysis: Descriptive Statistics	Characterize overall distribution of variable of interest	Calculate mean, top and bottom 20% of each variable
Descriptive Analysis: Distribution Check	Visually inspect the overall distribution of variables of interest	Histogram, color by 20% minimum, maximum and around mean values.
Correlation	Identify candidate variables potentially associated with case duration and surface structural dependencies between variables	Pearson correlations between duration and variables; intercorrelation heatmap; exploratory *p*-values.
Mining & Analysis (Sect. 3.3)		
Regression: Variable reduction	Reduce redundancy among highly correlated predictors	Variance Inflation Factor (VIF) analysis
Regression: Multivariate regression modeling	Estimate joint associations with case duration while controlling for other factors, yielding a parsimonious set of candidate influences.	Linear regression (Ordinary Least Squares); backward elimination; model fit via adjusted R^2 and F-test.
Auxillary Statistics: Descriptive Statistics	Compare summary measures of the variable of interest and key process characteristics across analytically defined subgroups.	Comparable values such as counts of occurance, mean, median by subgroup and whole sample.

first branch encompasses a data-driven identification of relevant factors, and the second branch is based on expert opinion.

Data-driven initiation

Data-driven initiation consists of three steps. First, the event log is transformed into a structure suitable for subsequent statistical analysis by generating features (Zandkarimi et al. 2020). For instance, the occurrence frequencies of each activity per case, duration taken per activity, and the presence of directly-follows pairs in a case are typical (case-level) features (Lepsien et al. 2023). The specific choice of features depends on the use case and analysis goal. Generally, analysts should initially generate a broad set of features covering diverse aspects of the data, and later reduce this set by selecting the most relevant features. Still, generating multiple features with high overlap (e.g., activity presence and activity frequency) should be avoided because it introduces unnecessary complexity, and such features will inevitably be removed in feature selection because of high intercorrelation.

After data transformation, an initial descriptive analysis is performed. This includes examining properties of the data and features that are relevant to select appropriate statistical methods in subsequent analysis (e.g., normality). While there are many options for exploring the data, we recommend beginning with histograms and boxplots of the main variables of interest. The results of the descriptive analysis are discussed and interpreted together with domain experts to develop additional ideas for subsequent analysis. The discussion also acts as an early plausibility check to validate that the data was extracted and transformed correctly.

The third step is the correlation analysis. To determine whether Pearson's or Spearman's correlation is appropriate, the response variable (also referred to as the dependent or outcome variable), e.g. case duration, is first tested for normality. In the context of an event log, the Shapiro–Wilk test should be applied when the number of cases is ≤ 50, whereas the Kolmogorov–Smirnov test is recommended for larger samples (Mishra et al. 2019). Correlation is calculated both from features to the analysis objective and

between features. This is done to identify candidates with a strong relationship to the analysis objective (e.g., case duration) and to examine the relationships between all the variables. When a large number of variables are considered, heatmaps that incorporate significance levels (e.g., by shading cells according to p-values) provide an effective visual summary of the correlation structure.

Expert opinion initiation

The second initiation branch is driven by expert opinions, which are through interviews. In most cases, these interviews should be conducted in a semi-structured manner (Knott et al. 2022). Semi-structured interviews typically rely on a topic guide, which consists of a set of broad topics to discuss during the interview, but allow for flexible probing and open-ended discussion (Knott et al. 2022). To guide the identification of influential factors, analysts can, for instance, rely on process mining context frameworks (Koschmider et al. 2019; Franzoi et al. 2025). Additionally, interviews should include open-ended questions that prompt experts to contribute ideas that extend beyond the scope of the topic guide, which might in some cases also trigger repeat interviews with previous interviewees (Gioia et al. 2013). Analysts perform an initial examination of the results from the expert interviews. This primarily encompasses a pre-screening with descriptive statistics to estimate importance.

An important consideration with expert interviews is the possible bias introduced by the varying perspectives of different stakeholders involved in a process (Dumas et al. 2018). Most often, such bias is unintentional, but in extreme cases, opportunistic stakeholders might introduce it deliberately, e.g., by hiding specific information, because they follow personal goals that do not coincide with the goals of the process or its analysis (Adamo et al. 2018; Dumas et al. 2018). To control for bias, interviews should be conducted with multiple experts, preferably having heterogeneous backgrounds (e.g., role in the process, organization, experience).

Mining & analysis

The aim of the *Mining & Analysis* phase is to analyze the datasets and prepare analysis results for interpretation and discussion. First, the number of features resulting from data-driven initiation needs to be reduced to identify the most promising candidates. Dimensionality reduction techniques such as principal component analysis or truncated singular value decomposition can be used to reduce the number of features (Zandkarimi et al. 2020). However, this impedes interpretability, because the resulting, transformed features are linear combinations of multiple input features. Thus, analysts should carefully consider whether complex dimensionality reduction techniques are necessary, or if simpler but more explainable techniques for feature reduction are sufficient. For instance, features can be filtered if they show high intercorrelation with other features (in which case only one of the correlated features should remain), or their correlation with the analysis objective has high p-values or weak correlation strength (low coefficient values indicating effects that are not important in practice). We recommend controlling for multicollinearity by calculating the variance inflation factor (VIF) for all predictors and iteratively removing variables with the highest VIF values until all remaining predictors have a VIF below 10 (Thompson et al. 2017). The list of removed variables should then be reviewed with domain experts to decide which predictors to retain, as removing

variables solely based on VIF scores may result in excluding the more interpretable variable from a highly intercorrelated pair (Thompson et al. 2017).

After eliminating highly intercorrelated variables, a regression model can be constructed with all remaining features. To identify the most statistically significant predictors, a backward feature elimination procedure is applied to the regression model. The result of this is a reduced shortlist of bottleneck candidates. This list is provided directly as a result artifact for the next phase. The shortlist is then merged with the candidates resulting from expert opinion initiation, and the merged list is used to guide further analysis.

Before process mining can be applied, further event log processing is often required for highly variable processes, as otherwise the results of process mining techniques, e.g., process models, are overly complex and hard to interpret (Lu and Fahland 2017; Zandkarimi et al. 2020). Splitting the event log into subsets of similar cases enables the discovery of models that are simpler and easier to interpret (Zandkarimi et al. 2020). This can also help uncover behavioral patterns that only exist in a certain subset of the event log, which are not visible in the global view encompassing the full event log (Lepsien et al. 2023). Typically, different local patterns can be observed in each subset (Lepsien et al. 2023).

Accordingly, as the approach primarily focuses of bottleneck analysis, different splits of the event log are constructed based on the merged list of bottleneck candidates. Depending on the candidate factor, these splits can be binary (e.g., expert witness present or not present) or based on a binning of values (e.g., 20% fastest and 20% slowest cases). For each split, a process model is discovered and enhanced with additional annotations, e.g., activity durations (Unger et al. 2021). Additionally, auxiliary statistics are prepared for each split of the event log and discovered model to support interpretation and discussion. The models enable the comparison of the process paths and (local) patterns between different splits (Ahmadi et al. 2026), which helps to interpret the influence of each candidate factor in the procedural context.

Evaluation

The evaluation phase involves comparing the descriptive statistics and the derived process models to assess differences between cases affected by bottlenecks and those that are not, aiming to identify any structural differences that may explain prolonged case durations. Measures and descriptive statistics (e.g., mean case duration), which are calculated for each process model, help quantify the impact of the identified bottlenecks. Analysis results are interpreted and discussed together with domain experts. Including domain experts ensures that results are interpreted correctly, and is also done to verify and validate analysis outcomes (van Eck et al. 2015, Ahmadi et al. 2026). Based on this, insights and ideas for process improvement are derived (van Eck et al. 2015).

Case study: lawsuit handling in a German social court

To demonstrate the feasibility and usefulness of our analysis approach, we applied it in a real-world case study concerning the handling of lawsuits in a German social court. This section summarizes the use case and how we instantiated our approach to plan and conduct analysis. First, Sect. 4.1 provides an overview of the analyzed process and its context (phase 1 of PM^2). Then, Sect. 4.2 describes the extraction and preparation of the event

log (phase 2), and general data cleaning and anonymization (partially phase 3). Finally, Sect. 4.3 details the instantiation of the subsequent phases of our analysis approach. At the time of this paper's submission, phase 6 was still ongoing, with domain experts leading the implementation of identified process improvements into judicial practice.

Anatomy of the lawsuit handling process

The *planning* of the project (Phase 1) was initiated via a series of interviews and discussions with domain experts, with the aim of (1) selecting the specific process to be analyzed, (2) achieving a general understanding of the process, and (3) setting the goals of the analysis. From these discussions, it was decided that the project should focus on the process by which lawsuits are handled in the court, with the goal of identifying activities and other factors associated with process inefficiencies and increased case durations.

Figure 3 presents an abstract overview of the analyzed process. Generally, the process unfolds in three stages. The first stage, *case initiation*, encompasses all actions taken before an official lawsuit is filed, e.g., the plaintiff preparing a lawsuit individually or with assistance from a lawyer or court clerk. As this stage is executed by the plaintiff according to their personal decisions and independent of how the court handles its lawsuits, it is considered out of scope for our case study. Instead, the paper will focus on the subsequent stages, which are initiated when an official lawsuit is submitted and then executed by the court and its judges. In stage 2, *review and case evaluation*, the judge informs the defendant of the lawsuit, examines the case file and performs an investigation to collect the information necessary for a ruling. While in other fields of law, e.g., civil law, evidence is typically provided by the opposing parties, in Germany, specifically in social law the judges themselves are responsible for gathering all required evidence. This may involve requesting additional information from institutions, the active (plaintiff) and passive (defendant) parties, expert witnesses, or other sources. Based on the investigation, the judge determines whether a hearing is necessary. If no hearing is required, a

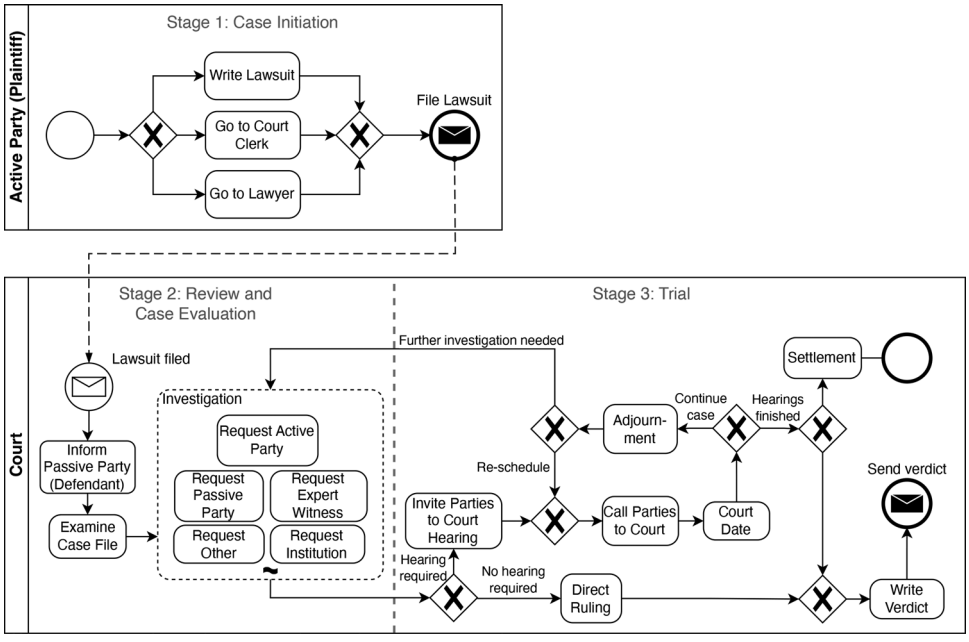

Fig. 3 BPMN model giving a high-level overview of the analyzed court process

direct ruling is issued, and a verdict is written and sent to the parties. If a hearing is required, the *trial* (stage 3) is initiated by inviting all relevant parties and scheduling a court date. At the court hearing, the case can be resolved in multiple ways. A verdict may be issued, the parties may reach a settlement, or the court may decide to adjourn the proceedings, potentially returning to the investigation phase for further evidence gathering. Furthermore, the plaintiff can withdraw their lawsuit at any point in the process.

Compared to the trial stage, which is fairly structured and based on strict procedural rules, the investigation stage is highly complex and heterogeneous, mainly due to two reasons. Firstly, the constitutionally guaranteed independence of the judiciary gives judges a great deal of freedom in the way they conduct investigations. Secondly, each investigation requires case-specific steps, which might, for instance, involve concurrently and repeatedly identifying and calling witnesses, requesting expert opinions and coordinating with institutions. While this is challenging for process mining algorithms (see Sect. 2.1.1), process mining might still produce valuable insights about the structure of the lawsuit handling process, and together with other process analytics techniques identify patterns in procedural delays and bottlenecks that may otherwise go unnoticed (Caponecchia et al. 2025).

Dataset extraction and preparation

We extracted data from the court information system. Data was extracted in PDF format with personal information redacted to ensure privacy. The raw dataset consisted of 260 cases from three chambers on the same topic within a single German social law court. Chambers are used as organizational units to classify and manage cases. Each chamber focuses on a specific social law topic (e.g., health insurance, social benefits or pensions), with multiple chambers covering each topic. Cases are assigned to one of the chambers within the relevant topic. Chambers are assigned to judges and clerks, with each judge and clerk responsible for multiple chambers across different legal topics. With this structure, it is impossible to know in advance which judge or clerk will be assigned to one specific case.

The data originates from a single judge, who typically oversees five to six chambers, meaning that this dataset represents only a subset of the judge's total caseload. Optical Character Recognition (OCR) was used to extract the document text, which was organized into an event log according to the tabular structure of the documents. In the dataset, a single timestamp is recorded for each activity occurrence, commonly indicating only an end date rather than a precise timestamp. This limits the granularity of time-based analyses and the accuracy of calculated activity durations. Depending on the analysis goals, the occurrence of two activities on the same date might also imply uncertainty about their order (Leemans et al. 2023), which might require special handling (Lepsien et al. 2025; Reiter et al. 2025). As the analysis focuses on the overall durations of cases, which typically range from multiple months to years, the impact of timestamp imprecision was negligible in our use case. We have added a detailed description of the activities recorded in the event log. In court processes, each activity involves one or more actors. These actors are judges, clerks, active or passive parties, expert witnesses, physicians forwarding patient-related documents, other (or unknown actors when the performer cannot be identified. Activities are further characterized by the type of action performed, which can be classified (by increasing level of effort) as: *take note of*, *file into*

the case file, *send*, *read*, and *write*. This classification is intended to provide more information about the activities and the involvement of the organization for readers outside the legal domain.

After extraction, the event log was further processed in consultation with domain experts to ensure anonymity, remove noise, and raise it to an abstraction level appropriate for analysis (phase 3). All remaining personal identifiers, such as expert witness names, were removed from the log to ensure anonymity. Additionally, timestamps were systematically perturbed to further enhance data privacy. Originally, the event log contained 22,664 recorded events and 290 unique activity labels. To further improve the quality of the event log, the domain experts reviewed the list of unique activity labels. This revealed a number of synonyms, i.e., distinct activity labels with the same semantics (Sadeghianasl et al. 2020) (e.g., *Proof of Delivery AP* and *Proof of Delivery AP Envelope* were merged into *Proof of Delivery AP*; similarly, *Court Questions* were merged into *Court Order*). Additionally, the data contained events with activities logged at varying levels of granularity (van Zelst et al. 2021; Beerepoot et al. 2023). Based on the expert review, synonymous activity labels were merged, activities were abstracted to a consistent granularity, and terminology was standardized across cases. This refinement reduced the number of unique activity labels to 59. Finally, duplicate events were removed. Duplicate events entered the log mainly due to technical reasons, e.g., letters to parties that were opened multiple times caused repeated events on the same day referring to the same letter. These steps collectively reduced the dataset to 19,947 events. The anonymized and processed dataset with 260 cases, 19,947 events and 59 unique activities is provided online (Aleknonyte-Resch et al., 2025a).

Instantiation of the analysis approach

In the following, we summarize the instantiation of our analysis approach from Sect. 3 by describing how we specified its phases – namely, *data processing* (phase 3, Sect. 4.3.1), *mining & analysis* (phase 4, Sect. 4.3.2), and *evaluation* (phase 5, Sect. 4.3.3) – for application in our use case.

Data processing

Data processing started from the cleaned and anonymized event log (see Sect. 4.2). To further enrich the event log, we calculated the case duration, the number of unique activities per case, the total number of events per case, and the count of occurrences for each activity class. For the descriptive analysis, we examined the frequencies of activity classes and created a histogram depicting the distribution of case durations. The results were reviewed and discussed with domain experts. A correlation analysis was then conducted across all features to identify potential relationships with case duration and examine intercorrelations. Multiple heatmaps were derived, which were discussed with domain experts. For the expert opinion initiation, we interviewed five judges from different social courts to identify variables and context factors that these judges perceive as bottlenecks.

Mining & analysis

For the data-driven initiation branch, we reduced the features by means of VIF and built a regression model and applied backward elimination until all variables in the regression

were nominally significant ($p < 0.05$). This resulted in a shortlist of possible bottlenecks. The resulting shortlist of possible bottlenecks was merged with the results of the expert opinion initiation into a combined set of bottleneck candidates. For the sake of simplicity, in this paper we focus on the two most promising bottleneck candidates. Data subsets were then created by splitting cases into groups with and without these bottlenecks, allowing us to assess whether specific procedural patterns or case attributes were strongly associated with extended case durations. Additionally, the dataset was segmented based on case duration, deriving process models for the 20% fastest cases, the 20% slowest cases, and the 20% of cases closest to the mean duration. Process models were built from these subsets using Disco (Fuzzy Miner). Additionally, we gathered auxiliary statistics on the process models, e.g. mean and median case durations, and the total number of unique activities. An initial interpretation of the results was conducted without the domain experts to prepare the discussions.

Evaluation

For evaluation, we used the process models and auxiliary statistic generated in the previous phase. Particularly, we examined the case duration, the number of events per case, the number of unique activities, and the number of directives, to analyze and quantify the impact of identified bottlenecks. Directives are formal instructions or decisions issued by judges to advance a case. They are the primary tool judges use to manage proceedings, and their frequency reflects the judicial workload involved in a case. Written statements by active party (AP) are formal submissions presenting arguments, evidence, or responses in the case. The process model visualizations and statistical findings were discussed with the judges to validate the results and ensure their practical relevance. Based on this discussion, ideas for *process improvements and support measures* (phase 6) to optimize case handling and reduce inefficiencies in court proceedings were formed.

Results

This section presents the evaluation results of the exploratory analysis approach for the specific use case of social courts, combining initial expert interviews with statistical analyses, regression analyses and process model comparisons. In Sect. 5.1, we summarize delays perceived by judges and list the perceived potential bottleneck candidates (factors). In Sect. 5.2, we first examine the distribution of case durations and then consider the bivariate correlations and a multivariate regression model to identify factors associated with longer or shorter case durations. In Sect. 5.3, we use the candidate factors from interviews and regression analysis to derive subgroup-specific process models and the corresponding descriptive statistics to illustrate whether and how the shortlisted factors relate to differences in procedural trajectories. Finally, Sect. 5.4 discusses the results with domain experts to assess plausibility, interpretability, and practical relevance.

Bottleneck candidates

Initial interviews with five judges from various social courts identified several perceived bottlenecks possibly increasing case durations. These included the following five perceived bottlenecks: the involvement of expert witnesses, the need to send reminders, the request for medical findings, treatment reports, and whether a court date was required.

Regarding the inclusion of expert witnesses, it was argued that it introduces a structured delay. While expert witnesses are typically given a fixed response time to submit their report, they sometimes require additional documents, which can further extend their response time. Similarly, when reminders need to be sent, judges noted this could indicate a pattern of late responses, i.e., the involved party could tend to exhaust deadlines throughout the entire process.

Additionally, requests for medical findings and treatment reports require collecting additional documents which involves multiple actors and can further delay proceedings. This is particularly tedious because the judge must wait for all requested information and can only then revisit the case file. Finally, not all cases require a court date. Judges believed that cases where a verdict could be written immediately should be resolved faster, as Stage 3 (the trial stage, see Fig. 3) would be significantly shorter without a hearing.

Figure 4 shows the distribution of case durations in days. Visually, the distribution appears roughly normal, though slightly right-skewed due to the natural lower bound at zero and the presence of a few exceptionally long cases. The Kolmogorov–Smirnov test ($D = 0.066,\ p = 0.2074$) did not reject the null hypothesis of normality, allowing us to proceed with a Pearson correlation analysis.

In the data-driven initiation branch, 24 out of 62 variables exhibited a Pearson correlation p-value less than 5×10^{-5}, indicating a possibly statistically significant relationship with case duration. However, since our analysis was exploratory, no significance threshold was set. Figure 5 shows the correlation of the case duration with these variables and their intercorrelations. A number of strong intercorrelations between certain variables can be observed. This suggests procedural dependencies. For example, there is a strong correlation (0.82) between expert witness report and order of evidence. An order of evidence is necessary for the expert witness to write a report, if it is not submitted in the beginning of the case, the judges ask for them, making this dependency structural.

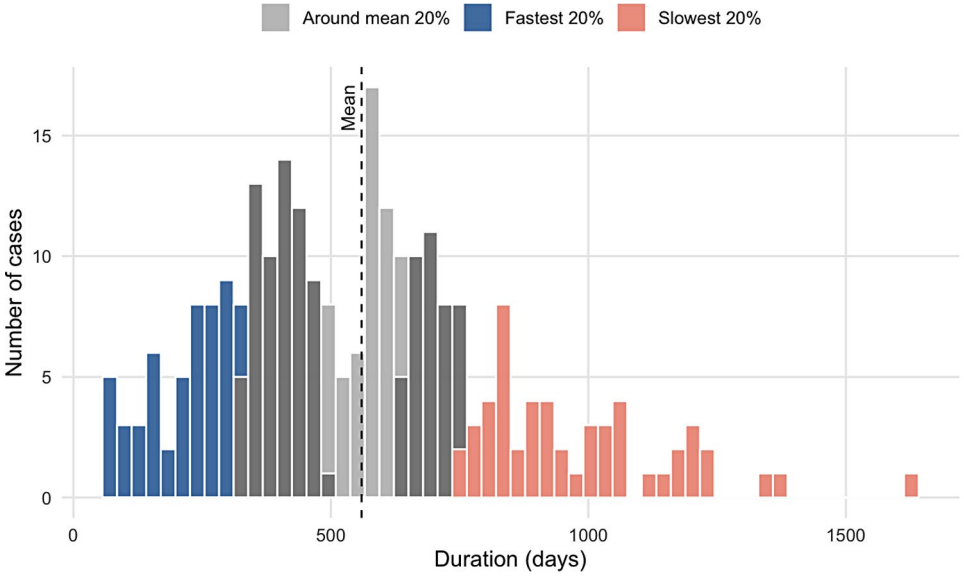

Fig. 4 Distribution of case durations in days. Cases are categorized into the 20% fastest (blue), slowest (red), and closest to the mean (light gray) duration. The dashed vertical line indicates the mean case duration

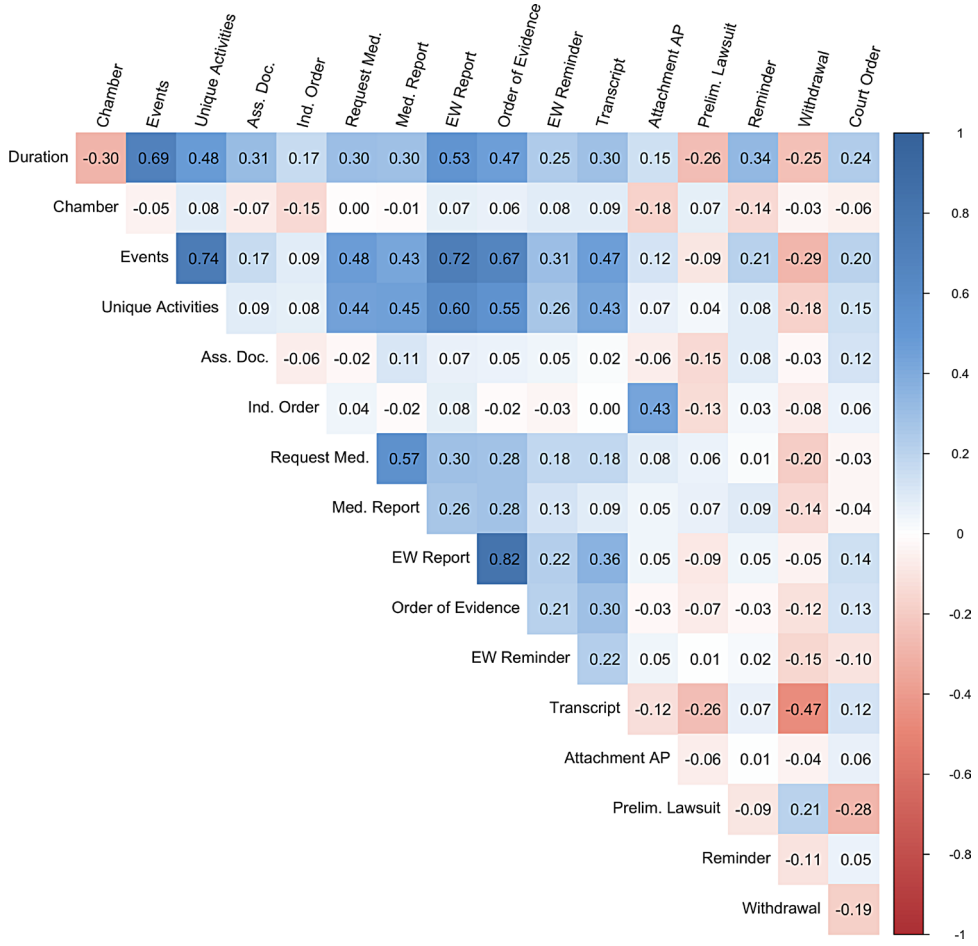

Fig. 5 Correlation heatmap with the case duration and intercorrelation of selected activities. Numerical values represent correlation coefficients

The highest correlation coefficients with case duration were observed for the total number of events (0.69), the number of unique activities (0.48), and the presence of an expert witness report (0.53). The strong correlation with the number of events and the number of unique activities is expected, as cases with a higher number of distinct procedural steps tend to be more complex, requiring additional interactions and decisions. Similarly, the presence of an expert witness report indicates greater case complexity. Since obtaining such a report necessitates an external review, it inherently extends case duration due to dependencies on third-party availability and evaluation time.

In contrast, the lowest correlations with case duration were found for case withdrawal (–0.25), preliminary lawsuit submission (–0.26), and chamber number (–0.30). Withdrawals shorten processing time as no formal verdict is required. Withdrawal correlates slightly with preliminary submissions, suggesting these cases (often filed by associations) could have been frequently withdrawn due to either lack of merit, or presence of an expert (lawyer) who has handled multiple similar cases. The correlation with chamber number is likely spurious as chamber numbers do not have a meaningful order, as there is a protocol, which states that cases are assigned randomly to the chambers.

Interestingly, the activity *send reminders* shows no correlation with other activities but is moderately correlated with case duration (0.34, $p = 3 \times 10^{-8}$). This suggests that

parties who require reminders may tend to delay the overall process. Such findings point towards the fact that bottlenecks may not always stem from the procedural structure itself, but from the behavior of involved parties.

Statistical analysis of influences on case duration

To identify key factors influencing case duration, we first applied VIF analysis to remove variables with very high multicollinearity. Before excluding any variable, we examined its intercorrelation with others and consulted domain experts to decide which of the correlated variables to retain. This process yielded 47 variables from the correlation analysis, which were included in a regression model. After a backward elimination procedure, 9 variables remained nominally significant and were thus identified as possible bottlenecks. The regression results, including estimates, standard errors, and p-values, are presented in Table 3. The estimate values can be interpreted as the number of days a given factor alters the case duration on average.

The results indicate that the inclusion of an assessment document in a case file is associated with a 128-day increase in case duration. As assessment documents can be submitted at the beginning of the process alongside the lawsuit, this may indicate larger, more complex cases. Similarly, if an expert witness report is required, the case duration is extended by 108 days, reflecting the additional time needed for the external assessment. For each additional activity class, the case duration is prolonged by almost 12 days. This indicates that the more diverse the activity classes are, the longer the case duration becomes. This could possibly be due to the fact that a higher number of unique activity classes reflects greater case complexity and procedural breadth, which typically entails additional coordination across actors and procedural steps and therefore prolongs the overall case duration. Furthermore, each written statement from the active party is associated with an average increase of 26 days in case duration. According to domain experts, this is expected, as the passive party is typically granted four weeks to respond to such submissions. This may suggest that the passive party often uses the full legally allotted response time. In addition, each reminder is associated with an average increase of 42 days in case duration.

Conversely, certain factors were associated with shorter case durations. The submission of a preliminary lawsuit shortens case duration by 67 days, possibly due to streamlined preparation by social welfare organizations or because such cases lacked merit and were therefore more quickly resolved. Domain experts noted that while some active parties do not have legal representation, having a power of attorney (typically a lawyer)

Table 3 Regression after backward procedure. Adjusted R^2: 0.595, p-value of F-statistic: 2.2×10^{-16}.

	Estimate	Std. Error	Pr($>\|t\|$)
(Intercept)	125.430	65.898	0.05814
No. Unique Activities	11.576	2.875	7.50×10^{-5}
Assessment Documents	127.829	30.755	4.44×10^{-5}
Expert Witness Report	108.121	19.870	1.26×10^{-7}
Power of Attorney	−105.214	28.002	2.14×10^{-4}
Written Statement Active Party	25.964	3.677	1.63×10^{-11}
Submission of Preliminary Lawsuit	−67.065	24.518	6.68×10^{-3}
Reminder	41.701	10.225	6.10×10^{-5}
Attachment by Expert Witness	−65.333	28.253	2.16×10^{-2}
File inspection	−51.601	16.412	1.87×10^{-3}

shortened case duration by an average of 105 days. File inspection, which is almost always conducted by lawyers and is always initiated by the active party or their lawyer, reduced case duration by 52 days. This is likely because the active party becomes better informed, requiring judges to provide fewer explanations, thereby streamlining the process. Interestingly, attachments submitted by expert witnesses were associated with a 65-day reduction in case duration. Such attachments may indicate a more thorough expert report or reflect the expert's detailed reporting style; in either case, the additional information appears to facilitate faster case resolution. Finally, case withdrawals shorten the process by 67 days, which is expected as withdrawals effectively bypass all remaining procedural steps.

Procedural variations

Process models were derived from subsets of cases, where the subsets were defined based on the variables that remained nominally significant in the regression analysis above. In order to examine the impact of these factors on procedural variations, process models were visualized separately for cases with and without each significant variable. To ensure meaningful process visualization, a filter was applied in agreement with domain experts, trimming the cases to sequences beginning with a (preliminary) lawsuit filing and ending in either a (direct) court ruling, declaration of case closing, declaration of settlement or withdrawal, reducing the full dataset to 17,953 events. Due to space constraints, and in consultation with domain experts, we selected four process models to present—distinguishing cases with and without expert witnesses and with and without a power of attorney. For illustration, Figure 6 shows the process model for cases without expert witnesses, which is clear and easy to interpret, unlike the complex spaghetti model observed when expert witnesses are involved (see Appendix A). Process models for cases without a power of attorney, while appearing clearer at first glance, reveal a high frequency of interactions in which judges must contact the active party directly.

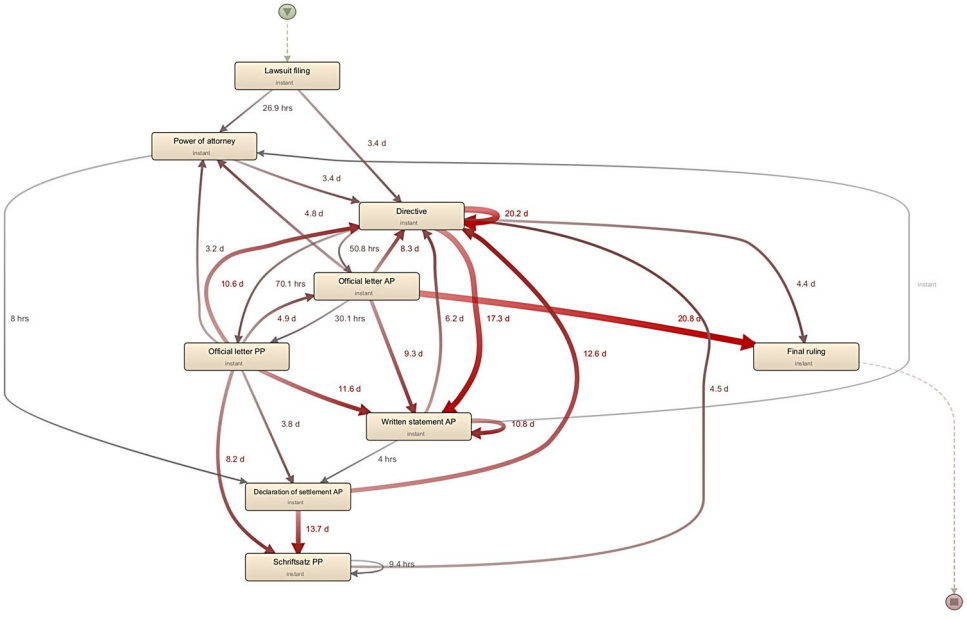

Fig. 6 Process model visualizing mean duration of the log subset containing only cases not involving expert witnesses

Table 4 Descriptive statistics for case subgroups

		20% Cases that are			Expert Witness		Assessment Documents		Power of Attorney	
	Total	Fastest	Around Mean	Slowest	Yes	No	Yes	No	Yes	No
Number of Cases	260	52	52	52	198	62	38	222	219	41
Mean Events per Case	77	46	80	109	87	64	90	74	77	77
Number of Activities	59	52	55	51	56	44	50	57	59	50
Median Case Duration (months)	18	8	19	30	20	10	25	17	17	21
Mean Case Duration (months)	18	7	19	32	21	11	25	17	18	23
Directives per Case	15	8	16	23	17	9	18	14	15	16
Written Statement AP per Case	6	4	6	9	7	4	7	6	6	5

In contrast, models for cases with a power of attorney are more complex and exhibit a greater variety of activities, yet these activities occur in a more logical manner, according to domain experts. Both model visualizations can be found in Appendix A.

Table 4 provides a comparison of case durations, event counts, and judicial involvement across different case subgroups. Due to space constraints, we again focus on subsets based on the presence of: expert witnesses, assessment documents, power of attorney and case duration categories (fastest, slowest, and around the mean). Across all subgroups, mean and median case durations are very similar by subgroup, suggesting that the data within each subgroup is approximately normally distributed, meaning there is no strong indication of skewness or extreme outliers.

The presence of an expert witness has a substantial impact on case duration. Cases without expert witnesses have a mean duration of 11 months, whereas cases with expert witnesses average 21 months. This discrepancy is further reflected in process complexity: cases without expert witnesses have fewer unique activities (44 vs. 56), mean events per case (64 vs. 87), and directives per case (9 vs. 17). This suggests two conclusions: first, cases requiring expert witnesses tend to be more complex, as they involve additional procedural steps and evidence review. However, the higher number of directives in cases with expert witnesses indicates that further investigation might be required even after contacting an expert witness. As the number of written statements by the active party are also higher when an expert witness is needed(4 vs. 7). This suggests a potential inefficiency, confirmed by domain experts: if judges could gather all necessary information for expert witnesses earlier in the process, it might be possible to reduce delays and streamline cases.

The presence of assessment documents correlates with longer case durations. Cases with assessment documents have a mean duration of 25 months, whereas those without take 17 months on average. Additionally, cases with assessment documents involve more events (90 vs. 74) and directives (18 vs. 14) (see Table 4). Assessment documents can serve as an indirect indicator of case complexity, and unlike expert witness involvement, this complexity is already apparent in Phase 1 (when the lawsuit is filed). According to domain experts, the underlying reason for increased complexity can stem either from the intrinsic nature of the case itself or from the involvement of a lawyer.

Subsequently, comparing the fastest, average and slowest 20% of cases reveals clear differences in process length and complexity. The mean case duration for the fastest

cases is 8 months, whereas the slowest average 23 months, nearly three times longer. The slowest cases have more than twice as many events per case (109 vs. 46) compared to the fastest cases. This suggests that the primary reason for extended case duration is not necessarily waiting times, but rather additional procedural steps that are required. This is further supported by the number of directives and written statements by the active party per case, which reflects the level of judicial and active party involvement. The fastest cases require significantly fewer directives per case (8), half of the average cases (16), whereas slowest cases require 23 directives on average. This indicates that more complex cases demand substantially more input from judges. Identifying cases likely to require additional procedural steps early in the process may help courts allocate resources more effectively, potentially mitigating extensively long case durations.

Expert validation

In Phase 5, the results were discussed with domain experts to validate their practical relevance and interpretability. The judges confirmed that the findings aligned with their professional experience and expectations, reinforcing the credibility of the analysis. The most interesting results for the domain experts were the strong effects of expert witnesses, assessment documents and power of attorney. While they had already observed that cases involving expert witnesses and assessment documents tended to take longer, the magnitude of these effects (108 days longer for expert witnesses and 128 days longer for assessment documents) was particularly impressive. The quantified estimate of these effects provided them with a better understanding of procedural delays. The role of attorneys in reducing case duration was particularly notable, with the presence of a power of attorney shortening proceedings by an average of 105 days. File inspections, which are also typically conducted by attorneys, reduced durations by approximately two months (51 days).

Collaboration with domain experts was essential for discussing possible causal relationships, as several insights only became apparent when combining statistical results with expert interpretation. For instance, the presence of assessment documents was recognized by experts as a strong early indicator of case complexity. Such documents could serve as a predictive signal in the initial phase to anticipate longer case durations and allocate resources accordingly. Experts also highlighted that approximately 16% of cases had no attorney involvement, which likely prolongs proceedings. They suggested that informing active parties early and clearly about the availability of state-provided legal representation could accelerate these cases.

Discussion

In this paper, we develop and apply a statistical, expert-integrated approach for using process mining and process analytics in non-business process contexts (specifically, judicial proceedings) where legal constraints, case heterogeneity, and the primacy of substantive outcomes limit conventional process redesign. We demonstrate the approach in a case study of a German social court by extracting event logs from digitalized court files and combining exploratory statistical analyses with domain expertise to identify bottlenecks and explain variation in case duration. The empirical findings illustrate how process analytics can make procedural dynamics transparent and support targeted improvement efforts without reducing judicial work to purely efficiency-driven

objectives. For example, we found that expert witness involvement and assessment documents are associated with substantially longer case durations, while attorney-related activities are associated with shorter durations. Finally, discussing these results with judges validates their plausibility and clarifies where process insights can translate into actionable interventions, underscoring the transferability of the approach to other domains in which event data exists but process goals and constraints differ from classical business settings.

In this section, we discuss the results across increasing levels of abstraction. We begin with the social court use case and interpret the empirical findings in light of judicial practice and constraints. We then generalize from the case study to reflect on the broader implications of the proposed statistical expert-integrated process mining approach for non-business process contexts. Finally, we discuss limitations and conclude by outlining directions for future research.

Insights from use case

In our use case, we demonstrated that process analytics is both feasible and valuable for analyzing court proceedings data in a German social court. By applying BPM techniques using our exploratory data analysis approach, we were able to gain first insights into the judicial process. Our findings were not only data-driven but also validated through discussions with judges, reinforcing the practical relevance of process analytics in the judicial domain. This collaborative approach helped to convince legal professionals of the potential benefits of process analytics, showing that process mining can enhance transparency, explain variability in case durations and identify bottlenecks in court proceedings. This motivation is not specific to our use case setting: many judicial systems operate under persistent capacity constraints and high caseloads, making transparency about procedural dynamics and avoidable delays particularly relevant. For example, in India, courts face approximately 4.3 million pending cases, about 0.8 million of which have been pending for over a decade (Sil and Roy 2020).

Our analysis compared perceived bottlenecks identified through expert knowledge with actual bottlenecks revealed by the data-driven approach, showing that while the presence of delays was expected, their magnitude was surprising. Cases involving expert witnesses and assessment documents extended case durations by an average of 108 and 128 days, respectively. Although assigning an expert witness is not a bottleneck in itself, it changes the process flow in ways that often prolong proceedings.

Interestingly, we also identified factors that significantly *shorten* case durations, such as the involvement of an attorney (−105 days) and the submission of attachments by expert witnesses (−65 days). The latter likely reflects more thorough and detailed expert reports, which reduce the need for follow-up requests and explanations. These findings suggest specific measures to accelerate proceedings: involving expert witnesses who provide comprehensive reports, and systematically informing active parties early (ideally at the time of lawsuit filing) about the possibility of state-funded legal representation.

By comparing the slowest and fastest cases, we found that process complexity, measured by the number of events, directives, and unique activities, could be a stronger determinant of case duration than waiting times alone. These findings, validated by domain experts, provided valuable insights into procedural inefficiencies and confirmed

that certain case attributes (such as assessment documents) can serve as early indicators of complexity.

Together with domain experts, we derived four actionable insights for improving court proceedings and reducing bottlenecks:

1. **Early identification of complex cases.** One key finding was the early identification of complex cases, particularly those involving expert witness reports or assessment documents, which significantly prolong case durations. Flagging such cases at the outset would allow courts to allocate resources more effectively and plan necessary procedural steps in advance.
2. **Streamlining information requests.** Since cases requiring multiple directives, expert witnesses, and extensive documentation handling tend to take longer, efficiency could be improved by streamlining information requests and ensuring that all necessary documents are collected as early as possible. Another recurring pattern was that cases in which reminders were issued often experienced systematic delays, suggesting that certain parties consistently exhaust deadlines. This highlights the importance of distinguishing between reasonable delays (e.g., necessary time for legal review or evidence gathering) and avoidable delays (e.g., late submissions or repeated reminder cycles), allowing targeted interventions where they are most effective.
3. **Informing about financial support and appointment of attorney.** The involvement of attorneys emerged as another important factor. Cases with attorney representation were, on average, resolved significantly faster. However, not all active parties can afford legal counsel. In such situations, the court can provide financial support and appoint an attorney. At present, active parties either already know about this option or are informed later by a judge or clerk. Systematically informing all active parties as early as possible (ideally at the time of filing a lawsuit) could reduce avoidable delays, accelerate proceedings, and benefit both the parties and the court.
4. **Formulating non-judicially binding guidelines for judges.** As described in Fig. 3, Stages 1 and 3 follow well-defined, structured workflows, Stage 2 is notably dynamic and subject to individual judicial discretion (particularly when expert witnesses are involved) resulting in a lack of a "happy path." Another key insight was the identification of specific activities, such as the inclusion of additional and assessment documents at the end of Stage 1 or the beginning of Stage 2, which are strong indicators of potential case prolongation and complexity. This finding suggests that non-judicially-binding guidelines could be developed to (1) streamline the process when expert witnesses are involved and (2) help judges recognize early signals of increased complexity, thereby enabling them to better plan and allocate their resources.

Overall, these insights not only affirm that BPM can be effectively applied to court proceedings but also provide practical, data-driven strategies that can support judicial decision-making and workflow optimization.

Applicability and boundaries of the approach

Beyond the specific empirical findings from the German social court, the central contribution of this study is a statistical, strongly domain-expert-supported approach for applying process mining in non-business process contexts. In such settings, process goals are multi-dimensional, constraints are normative (e.g., due process requirements

and judicial discretion), and many observed delays can appear to be dysfunctional *prima facie* but may be legally or substantively justified. Consequently, purely data-driven optimization risks misclassification of necessary procedural steps as inefficiencies and may produce recommendations that are neither legitimate nor adoptable (cf. Mannhardt 2022). This adoption risk is reinforced by concerns in public administrations about new technologies, including fears of workforce displacement and uncertainty about AI governance, accountability, and transparency (Wirtz et al. 2020). These concerns further motivate an expert-integrated approach that prioritizes interpretability and institutional acceptability alongside statistical validity.

Our approach addresses these challenges by coupling exploratory statistical analysis with continuous expert interpretation. Statistically, we use correlation analysis to screen for potential influences on case duration and a multivariate regression pipeline with multicollinearity checks to identify robust associations in the presence of structural dependencies between activities. Expert input is then used at each stage to (i) define meaningful variables and filters for event log construction, (ii) interpret intercorrelations as procedural dependencies rather than independent effects, and (iii) distinguish plausible mechanisms (e.g., case complexity or mandated response windows) from spurious associations. This integration is particularly important in non-business domains, where event logs reflect institutional and normative constraints and objectives warranting considerations in analysis design that significantly diverge from typical approaches guiding profit- or efficiency-maximizing behavior.

We primarily developed our analysis approach based on considerations from the judicial domain (Sec. 2.1), and accordingly, our evaluation is grounded in a social court use case. However, the constraints and requirements identified for the judicial domain (non-negotiable and tight quality constraints, strong decision-maker autonomy, high importance of stakeholder integration both for understanding as well as building trust) are characteristics that can be observed in a broader class of processes. Because the approach was intentionally designed at an intermediary level of abstraction between generic project management approaches such as PM^2 and specific domain or use case requirements, it can generally take the role of a blueprint that might potentially be transferred to related domains, albeit certainly requiring adjustments that take into account the specific analytical methods and unique expectations of the respective stakeholders.

For instance, the healthcare domain faces highly similar constraints on various levels (Rojas et al. 2016). Consider the individual treatment of patients in an emergency department: to ensure that each patient is treated thoroughly and individually, and given the cost constraints, any patient without an immediately critical condition must expect long waiting times. However, as even seemingly small differences in speed can substantially impact on treatment success (Juskeviciute et al. 2025) and urgency might be underestimated during triage, it is generally favorable to reduce all waiting times – but analysts need to keep in mind that overoptimization of treatment speed risks jeopardizing thoroughness. Hospitals also face many similar organizational issues, e.g., administrative friction, scheduling conflicts, and bottlenecks due to overloaded organizational units. Transferring our approach would require extended focus on rigorous statistical techniques, e.g., significance testing and controlling error rates for process mining, to reflect the increased expectations for robustness and reliability of results in the medical domain.

Another related domain that might benefit from an adapted version of our approach is public administration. In addition to strong similarity in terms of inflexible budget constraints and restricted redesign possibilities, public administration is also characterized by high barriers for technology adoption that are in interplay with lacking trust (Wirtz et al. 2020). Thus, even when considering the lower degree of autonomy in process execution in public administration, the focus of our approach to facilitate building trust makes it very relevant in this domain. Here, however, as process execution is less centrally orchestrated and more distributed than in the judicial domain, our approach would need to be extended towards the integration of broader groups of stakeholders.

Limitations

A key limitation of this study is that the use case stems from one social law court in Germany, focusing on chambers handling specific types of cases from the same judge. While this limits generalizability across courts, regions, and legal systems, it can also be seen as a strength, as the observed differences in case duration and process structure cannot be attributed to variation between judges or jurisdictions. Due to privacy constraints, substantial identifying information was removed from the event log to ensure anonymity. As a result, it was not possible to determine which specific clerks, attorneys, or expert witnesses participated in individual cases. Incorporating this information (while maintaining privacy) could enable object-centric analysis and more fine-grained analyses, such as assessing the impact of specific actors on case duration and process flow. Furthermore, the event log available from the court system contained only end dates for activities. While certain activities, such as sending invitations, are instantaneous and the most important aspect of the event log in court proceedings is the chronological sequence of the process, the duration of activities could provide deeper insights into bottlenecks and inefficiencies.

Future research directions

Looking to the future, judges expect that new technologies will shorten court proceedings (Dhungel and Heine 2024). The introduction of the electronic case file in Germany, in conjunction with BPM, has the potential to make proceedings more efficient and to identify process slowdowns at an early stage. Future work should focus on analyzing directive types, as different directives may impact case duration differently. LLMs could help extract and categorize directive content from PDF files, enabling a more detailed process analysis. Extraction of further information, e.g., duration of activities by means of meta data, would increase the quality of the event logs. For the legal domain, local LLMs are especially relevant as they enable processing sensitive data independent of external cloud services (Apaydin and Zisgen 2025; Reiter et al. 2025). Methodologically, future work should compare process discovery results across different miners (e.g., Inductive Miner, Heuristics Miner, and Fuzzy Miner) to assess the robustness of the observed process patterns and the extent to which model structure and interpretability depend on the chosen discovery technique. Additionally, reducing complexity in process mining for court proceedings is essential, as legal processes are highly heterogeneous. Simplifying event logs, grouping similar process variants, and filtering non-essential steps would make BPM more effective and accessible for judicial analysis (Lu and Fahland 2017). Lastly, the increasing availability of event data might also warrant the

development of sampling techniques with appropriate relevance characteristics for legal processes, which would facilitate the efficient analysis of large datasets (Fonger et al. 2025). Addressing these challenges will further optimize court processes, improve case management, and enhance transparency and interpretability (Dhungel and Beute 2024).

Supplementary information

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Supplementary Material 1

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Author contribution
M.A.R. and A.L. contributed to the conceptualization and methodology. M.A.R. conducted the formal analysis. F.E. collected the data. M.A.R. prepared the original draft of the manuscript. M.A.R., A.L., and A.K.D. reviewed and edited the draft. M.A.R. and A.L. created the visualizations. All authors reviewed and approved the final manuscript.

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Data availability
The event log generated and analyzed in the study is publicly available in the Mendeley repository: https://doi.org/10.17632/3mcvbrhr7c.

Declarations

Ethical approval
Not applicable.

Competing interests
The authors declare no competing interests.

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