Preserving Data Secrecy in Inter-organizational Process Mining

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Abstract. Inter-organizational business processes involve multiple independent organizations collaborating to achieve mutual interests. Process mining techniques have the potential to allow these organizations to enhance operational efficiency, improve performance, and deepen the understanding of their business based on the recorded process event data. However, inter-organizational process mining faces substantial challenges, including topical secrecy concerns: The involved organizations may not be willing to expose their own data to run mining algorithms jointly with their counterparts or third parties. In this paper, we introduce a novel approach that unlocks process mining on multiple actors' process event data while safeguarding the secrecy and integrity of the original records in an inter-organizational business setting. To ensure that the data acquisition, merging and elaboration phases are secure and that the processed information is hidden from involved and external actors alike, our approach resorts to decentralized trusted applications running in Trusted Execution Environments (TEEs). We show the feasibility of our solution by showcasing its application to a healthcare scenario.

Keywords: Collaborative Business Processes · Trusted Execution Environment · Encryption · Confidential Computing

1 Introduction

In today's business landscape, organizations constantly seek ways to enhance operational efficiency, increase performance, and gain valuable insights to improve their processes. Process mining offers techniques to discover, monitor, and improve business processes by extracting knowledge from chronological records known as *event logs*. Organizations record in these ledgers events referring to activities and interactions occurring within a business process. The vast majority of process mining contributions consider *intra-organizational* settings, in which business processes are executed inside individual organizations. However, organizations increasingly recognize the value of collaboration and synergy in achieving operational excellence. *Inter-organizational* business processes involve several independent organizations actively cooperating to achieve a shared objective. Despite the advantages in terms of transparency, performance optimization, and benchmarking that companies can gain from such practices, inter-organizational process mining raises challenges that make it still hardly applicable. The major issue concerns confidentiality. Companies are reluctant to outsource to their partners inside information that is required to execute process mining algorithms. Indeed, the sharing of sensitive operational data across organizational boundaries introduces concerns about data privacy, security, and compliance with regulations. *Trusted Execution Environments* (TEEs) can serve as fundamental enablers to balance the need for insights with the imperative to protect sensitive information in inter-organizational settings. TEEs offer secure contexts that guarantee code integrity and data confidentiality in external devices. *Trusted applications* are tamper-proof software objects running in these environments.

In this paper, we propose a novel approach for inter-organizational process mining that resorts to trusted applications to preserve the secrecy and integrity of shared data. To pursue this aim, we design a decentralized software architecture for a three-staged procedure: (i) the initial exchange of preliminary metadata (ii) the secure transmission of encrypted data amid multiple parties, (iii) the privacy-preserving merge of the shared information segments followed by the isolated and verifiable computation of process discovery algorithms on joined data. We evaluate our proof-of-concept implementation against synthetic and real-world-based data with a convergence test and memory effectiveness assessment.

The remainder of the paper is structured as follows: Sect. 2 provides an overview of related work inherent to the theme of inter-organizational process mining. In Sect. 3, we introduce a use case example that considers a healthcare scenario. The high-level architecture of our solution is presented in Sect. 4. Following on from this, we instantiate the addressed design principles in Sect. 5 focusing on the employed technologies, workflow, and implementation. In Sect. 6, we discuss our solution. Finally, we conclude and present directions for future work in Sect. 7.

2 Related Work

While inter-organizational process mining remains a consistent challenge, the academic literature has introduced a limited set of solutions. In the subsequent section, we enumerate these contributions, highlighting both their commonalities and distinctions in comparison to our work. The work of Müller et al. [12] pays attention to data privacy and security within third-party systems that mine data generated from external providers on demand. To safeguard the integrity of data earmarked for mining purposes, their research introduces a conceptual architecture that entails the execution of process mining algorithms within a cloud service environment, fortified with trusted execution environments. Drawing inspiration from this foundational contribution, our research work endeavors to design a decentralized approach characterized by organizational autonomy in the execution of process mining algorithms, devoid of synchronization mechanisms involvement taking place between the involved parties. A notable departure from the Müller et al. framework lies in the fact that, in our architectural design, each participating organization retains the discretion to choose when and how mining operations are conducted. Moreover, we bypass the idea of fixed roles, engineering a peer-to-peer scenario in which organizations can simultaneously be data provisioners or miners. Elkoumy et al. [6,5] present a framework called Shareprom, which, like our work, offers a means for independent entities to execute process mining algorithms in inter-organizational settings while safeguarding their proprietary input data from exposure to external parties operating within the same context. Shareprom's functionality is confined to the execution of operations involving event log abstractions [1] represented as directed acyclic graphs, which the parties employ as intermediate pre-elaboration to be fed into secure multiparty computation (SMPC) [3] sessions. In contrast to our approach, where the exchanged data consists of encrypted source logs, the reliance of Shareprom on this specific graph representation imposes constraints that may prove limiting in various process mining scenarios, as stated by the authors. Given that process mining encompasses a wide array of data types and representations, we acknowledge the potential need for alternative data structures in diverse process mining contexts. Moreover, SMPC-based solutions require computationally intensive operations and synchronous cooperation among multiple parties, which make these protocols challenging to manage as the number of participants scales up [13]. In our research work, the secure computation is contained within single elaborators and does not require constant communication with external parties once the input data is exchanged. In the course of our research endeavor, we are confronted with the imperative task of integrating event logs originating from different data sources and constructing coherent traces that describe collaborative process instances. Consequently, we engage in a comprehensive examination of various methodologies delineated within the literature, each of which offers insights into the merging of event logs within inter-organizational settings. Among the array of potential solutions in this domain, the work of Claes et al. [2] holds particular significance for our research efforts. This seminal study introduces a two-step mechanism operating at the structured data level, contingent upon the configuration and subsequent application of merging rules. Each such rule delineates the criteria, namely the relations between attributes of the traces and/or the activities, that two distinct traces must satisfy in order to be combined. In contrast, the research by Hernandez et al. [9] posits a methodology functioning at the raw data level. This approach represents traces and activities as *bags-of-words* vectors, subject to cosine similarity measurements to discern links and relationships between the traces earmarked for combination. An appealing aspect of this approach lies in its capacity to generalize the challenge of merging without necessitating a priori knowledge of the underlying semantics inherent to the logs under consideration. However, we have diverged from adopting this particular approach due to considerations inherent to computational overhead. This substantial computational load carries the potential to impact both the scalability and performance of our solution.

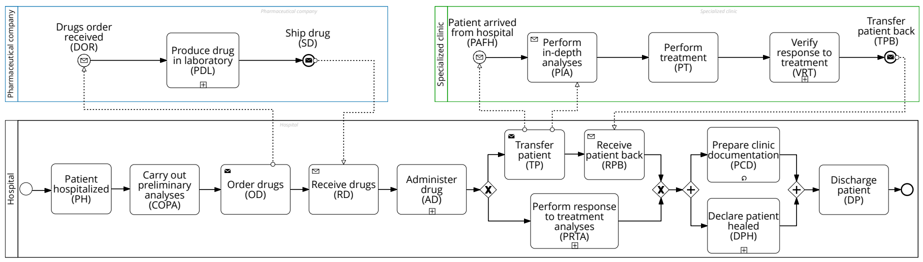


Fig. 1: A BPMN collaboration diagram of the healthcare scenario.

Table 1: Cases 312 and 711 recorded in the event logs of the Hospital, the Specialized clinic, and the Pharmaceutical company.

Hospital					
Case	Timestamp	Activity	Case	Timestamp	Activity
312	2022-07-14T10:36	PH	312	2022-07-15T22:06	TP
312	2022-07-14T16:36	COPA	711	2022-07-16T00:55	PRTA
711	2022-07-14T17:21	PH	711	2022-07-16T00:55	PCD
312	2022-07-14T17:36	OD	711	2022-07-16T02:55	DPH
711	2022-07-14T23:21	COPA	711	2022-07-16T04:55	DP
711	2022-07-15T00:21	OD	312	2022-07-16T07:06	RPB
711	2022-07-15T18:55	RD	312	2022-07-16T09:06	DPH
312	2022-07-15T19:06	RD	312	2022-07-16T09:06	PCD
711	2022-07-15T20:55	AD	312	2022-07-16T11:06	DP
312	2022-07-15T21:06	AD			

Pharmaceutical company		
Case	Timestamp	Activity
312	2022-07-15T09:06	DOR
711	2022-07-15T09:30	DOR
312	2022-07-15T11:06	PDL
711	2022-07-15T11:30	PDL
312	2022-07-15T13:06	SD
711	2022-07-15T13:30	SD

Specialized clinic		
Case	Timestamp	Activity
312	2022-07-16T00:06	PAFH
312	2022-07-16T01:06	PIA
312	2022-07-16T03:06	PT
312	2022-07-16T04:06	VRT
312	2022-07-16T05:06	TPB

$T_{312} = \langle$ PH, COPA, OD, DOR, PDL, SD, RD, AD, TP, PAFH, PIA, PT, VRT, TPB, RPB, DPH, PCD, DP $\rangle$

$T_{711} = \langle$ PH, COPA, OD, DOR, PDL, SD, RD, AD, TP, PAFH, DPH, PCD, DP $\rangle$

3 Motivating Scenario

For our motivating scenario, we focus on a simplified hospitalization process for the treatment of rare diseases that involves the cooperation of three parties: the Hospital, the Pharmaceutical organization, and the Specialized clinic. The process scheme is depicted in the BPMN diagram shown in Fig. 1. For the sake of simplicity, we describe the process through two cases. Alice's journey (case 312) begins when she enters the hospital for the preliminary examinations (the *patient hospitalized* event, PH). The Hospital then places to the Pharmaceutical company an order for the drugs (OD) needed to treat Alice's specific condition. Afterwards, the Pharmaceutical company acknowledges that the drugs order is received (DOR), proceeds to produce the drugs in the laboratory (PDL), and ships the drugs (SD) back to the Hospital. Upon receiving the medications, the Hospital administer the drug (AD), and conducts an assessment to determine if Alice can be treated internally. If specialized care is required, Alice is moved from the Hospital to the Specialized clinic (PAFH). When the patient arrives from the Hospital (PAFH), the Specialized clinic performs in-depth analyses (PIA) and proceeds with the treatment (PT). Once the Specialized clinic had completed the evaluations and verified the response to the alternative treatment (VRT), it transfers the patient back TPB. The Hospital receive the Alice patient back (RPB) and prepares the necessary clinic documentation (PCD). If Alice has successfully recovered, declares her as healed (DPH). When Alice's treatment is complete, the Hospital discharges the patient (DP). Bob enters the Hospital a few hours later than Alice. His hospitalization process is similar to Alice's. However, he does not need specialized care, and his case (711) is only treated by the Hospital. Therefore, the Hospital perform the response to treatment analyses (PRTA) instead of transferring him to the Specialized clinic. Both the National Institute of Statistics of the country in which the three organizations reside, together with the University that hosts/manages the hospital, wish to uncover information on this inter-organizational process for reporting and auditing purposes [?] via process analytics. The involved organizations share the urge for such an analysis, and wish to be able to repeat the mining task also in-house. The Hospital, the Specialized clinic, and the Pharmaceutical company have a partial view of the overall unfolding of the inter-organizational process as they record the events stemming from the parts of their pertinence. In Table 1, e.g., we show the traces 312 and 711 recorded by the Hospital (i.e., T^H_{312} and T^H_{711}), the Specialized clinic (i.e., T^S_{312} and T^S_{711}), and the Pharmaceutical company (i.e., T^C_{312} and T^C_{711}). Those traces are projections of the two combined ones for the whole inter-organizational process: $T_{312} =$⟨PH, COPA, OD, DOR, PDL, SD, RD, AD, TP, PAFH, PIA, PT, VRT, TPB, RPB, DPH, PCD, DP⟩ and $T_{711} =$⟨PH, COPA, OD, DOR, PDL, SD, RD, AD, TP, PAFH, DPH, PCD, DP⟩. Results stemming from the analysis of the local traces would not provide a full picture. Data should be merged. However, to preserve the privacy of the people involved and safeguard the confidentiality of the information, the involved parties cannot give open access to their traces to other organizations. The diverging interests (being able to conduct process mining on data from multiple sources without giving away the local event logs in-clear) motivate our research. In the following, we describe the design of our solution.

4 Design

In this section, we present the high-level architecture underlying our solution. We consider the main functionalities of each component, avoiding details on the employed technologies discussed in the next sections. Once we introduced the architecture, we focus on the `Secure Miner` component that represents the core of our contribution.

4.1 Architecture at large

Our architecture involves different organizational ecosystems characterized by one or more machines. An `Organization` may assume one of the following two different roles or both: *provisioner* if it delivers local event logs to be collaboratively mined; a *miner* whenever it applies process mining algorithms using local event logs retrieved from provisioners. Provisioner `Organization`s collaborate to achieve common objectives and compose inter-organizational business processes whose event logs are scattered across multiple places. Each provisioner produces event logs, recording the operations executed to complete its part in the inter-organizational business process. In Fig. 2, we propose the

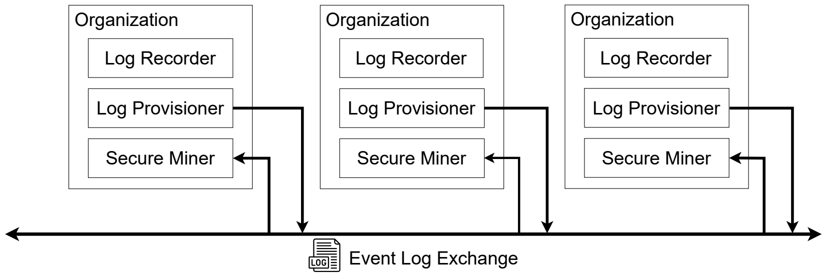


Fig. 2: High-level architectural overview.

high-level schematization of our solution. `Organizations` embed three main components, which we describe next: the `Log Recorder`, the `Log Provider`, and the `Secure Miner`. The maintenance of event logs is the core task performed by the `Log Recorder`. This component registers the events taking place in provisioner `Organizations`. The Hospital and the other parties in our running example record Alice and Bob's traces using their `Log Recorders`. The `Log Recorder` is queried by local `Log Providers` of the same `Organization` for event logs to be fed into remote `Secure Miners`. The `Log Provider` component delivers on-demand data to `Secure Miners`. It controls access to local event logs by authenticating data requests generated by miners. `Log Providers` reject demands from unauthorized parties and only permit `Secure Miners` to use the data. In our motivating scenario, the Specialized clinic, Pharmaceutical company, and the Hospital leverage `Log Providers` to authenticate the miner party before sending their logs. The `Secure Miner` shelters external event logs inside a miner ecosystem by preserving data confidentiality and integrity. We provide an in-depth focus on the `Secure Miner` as follows.

4.2 Secure Miner

The primary objective of the `Secure Miner` is to allow miners to securely execute process mining algorithms using event logs retrieved from provisioners such as the Specialized clinic, Pharmaceutical company, and the Hospital of our running example. `Secure Miners` are isolated components that guarantee tamper-proofing and data confidentiality. In Fig. 3, we show a schematization of a `Secure Miner` in which we distinguish four different subcomponents: the `Log Manager`, the `Log Requester`, the `Log Receiver`, and the `Log Elaborator`. Event logs belonging to provisioners are locked in the `Secure Miner`. We handle these data via the `Log Manager` which prevents malicious parties from having direct access to event logs. These unauthorized entities include any component of the miner `Organization` outside the `Secure Miner`. Referring to our motivating scenario, the `Log Manager` of the

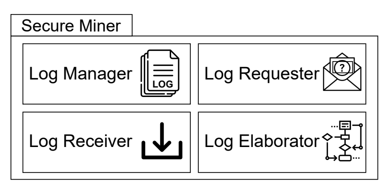


Fig. 3: Subcomponents of the Secure Miner.

miner isolates the traces of Alice and Bob from secrecy-attempting actions generated outside the `Secure Miner`. The `Log Requester` and the `Log Receiver` are the subcomponents that we employ during the event log exchange. `Log Requesters` send authenticable data requests to the `Log Provider` component of provisioners. The `Log Receiver` collects event logs sent by `Log Providers` and entrusts them to the `Log Manager`. The miner of our motivating scenario employs these two components to retrieve the traces of Alice and Bob from the provisioners. and to collect this information in the `Secure Miner`. The `Log Elaborator` provides the functionality to securely execute process mining algorithms inside the `Secure Miner`. When activated, the `Log Elaborator` merge the traces locked in the `Secure Miner` in order to have a global view on the inter-organizational process comprensive of activities executed by each the party involved. Aggregated data is employeed by the `Log Elaborator` as input of process mining procedures. Mentioning our motivating scenario, the `Log Elaborator` combine the traces referring to the cases of Alice (i.e., T^H_{312}, T^S_{312}, and T^C_{312}) and Bob (i.e, T^H_{711}, T^S_{711}, and T^C_{711}) generating the chronologically sorted traces T_{312} and T_{711} to be fed into mining algorithms.

5 Realization

In this section, we outline the technical aspects concerning the realization of our approach. Therefore we first present the enabler technologies through which we instantiate the design principles presented in Sect. 4. After that, we discuss the interaction workflow between the instantiated technologies. Finally, we show the implementation details.

5.1 Deployment

As follows, we bridge the gap between high-level system architecture and its practical realization. Fig. 4 depicts a *UML deployment diagram* [10] that aims to help with understanding the instantiated infrastructure.

In our solution, we make a differentiation between the computational *devices* designated for mining, denoted as `Miner Machines`, and those specifically associated with provisioners, identified as `Provisioner Machines`. To enhance clarity, we maintain the separation of these devices in the accompanying diagram. However, organizations have the flexibility to opt for integrated technologies that incorporate both mining and provisioning functionalities. We included the `Log Recorder`, the `Log Provider`, and `Secure Miner` (already discussed in Sect. 4) as abstract *components* of the diagram, whose manifestation are described as follow.

`Provisioner Machines` encompasses `Log Recorders` and `Log Providers` incorporating their core functionalities aimed at generating and transmitting event logs. Within the organizational context, we manifest the `Log Recorder` in the Process Aware Information System (`PAIS`), which plays a crucial role in managing various business processes, including accounting and resource management [4]. In

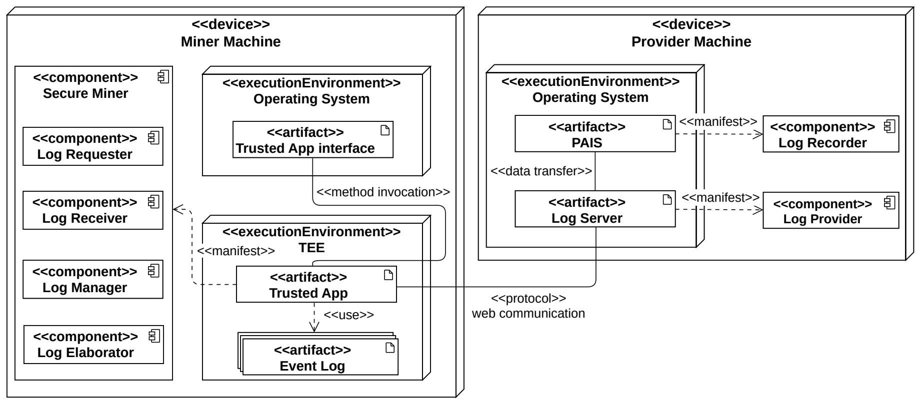
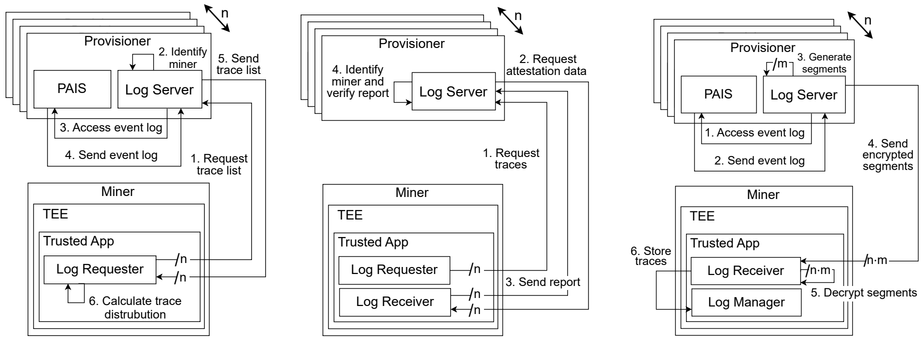


Fig. 4: UML deployment diagram.

our solution, the `PAIS` grants access to the `Log Server`, enabling it to retrieve event logs. The `Log Server`, on the other hand, embody the functionalities of the `Log Provider`, implementing web services amied at handling remote data requests and providing event logs to miners. `Log Servers` adheres to established web standards such as HTTP[1], FTP[2], and Goopher[3]. Both the `PAIS` and `Log Server` run on the top the `Operating System` of the `Provisioner Machine`.

The `Miner Machine` is characterized by two distinct *execution environments*: the `Operating System` and the Trusted Execution Environment (`TEE`). `TEE`s establish an isolated context separate from the normal `Operating System`, safeguarding code and data through hardware-based encryption mechanisms. This technology relies on specialized components of the `Miner Machine`'s CPU capable of managing encrypted data within a reserved section of RAM [**?**]. We leverage the security guarantees provided by `TEE`s to isolate a `Trusted App` responsible for fulfilling the functions of the `Secure Miner` and its associated subcomponents. The `Trusted App` consolidates the logic required for generating verifiable data requests, receiving external event logs, securely storing them within the `TEE`, and executing process mining algorithms. All procedures executed by the `Trusted App` are tamper-proof. The `TEE` ensures the integrity of the `Trusted App` code, protecting it against malicious manipulations and unauthorized access by entities operating within the `Operating System`. Additionally, we utilize the isolated environment of the `TEE` to securely store event logs from provisioner organizations within the `Miner Machine`. The `TEE` safeguards this sensitive information alongside a unique asymetric key couple used for attestation purposes (i.e., public and private keys), preventing exposure to the `Operating System`. Access to data located in the `TEE` is restricted solely to the `Trusted App`. Users interact with the `Trusted App` through the `Trusted App Interface`, which serves as

[1] https://www.w3.org/Protocols/rfc2616/rfc2616.html
[2] https://www.w3.org/Protocols/rfc959/
[3] https://datatracker.ietf.org/doc/html/rfc1436



(a) Initialization (b) Remote Attestation (c) Data Transmission

Fig. 5: Schematization of the initialization, remote attestation and data transmission phase.

the exclusive communication channel. The `Trusted App` offers secure methods, invoked by the `Trusted App Interface`, for safely receiving information from the `Operating System` and outsourcing the results of computations, maintaining a high level of data security.

The interaction between the newly introduced technologies is elucidated as follows.

5.2 Workflow

We separate the workflow into subsequent processes, namely *initialization*,*remote attestation*, *data transmission*, and *computation*. The parties involved in the workflow are a miner (i.e., an organization that executes process mining algorithms) and one or more providers (i.e., partner organizations that serve their event logs).

Initialization. In the initialization, the miner's `Trusted Application` requests preliminary information from the providers' `Log Server` concerning the event logs of an inter-organizational business process. After authenticating the sender, the involved `Log Server`s retrieve the local event log from the `PAIS` and respond to the miner by providing the list of trace IDs in the event log. Hence, the `Trusted Application` collects the responses and stores them in the `TEE`.

Remote Attestation.

Talk specifically of remote attestation

Data Transmission. Once recorded the preliminary information, the miner starts the data exchange. Therefore, its `Trusted Application` sends data requests to the `Log Servers`. The requests include as parameters the list of trace ids and the segment size. Subsequently, the `Log Server`s starts the *remote attestation* procedure, thanks to which they can verify that the sender of the log request: is a `Trusted Application` running inside a `TEE`; comes from a partner organization. This operation involves the exchange of additional messages between the `Log Server` and the `Trusted Application`. If the procedure is successful, the miner's identity is verified. Subsequently, the `Log Servers` retrieve the local event log and filter its traces according to the trace IDs sent by the `Trusted Application`. Filtered event logs are split into several segments containing traces whose dimension does not exceed the segment size parameter. `Log Servers` encrypts the segments and send each of them to the `Trusted Application`. The `Trusted Application` decrypts the received segments, extracts the traces, and stores them in `Event Logs` inside the `TEE`.

Computation. To start a computation routine, the `Trusted Application` needs all partner organizations to have delivered traces having the same ID. When this occurs, the `Trusted Application` merges external traces with the owned one. Assembled traces are used as parameters of process mining algorithms executed by the `Trusted Application` that presents the computation results to the users via the `Trusted Application Interface`.

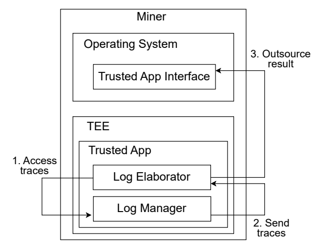


Fig. 6: Schematization of the computation phase.

5.3 Implementation

In this section, we expound the implementation of our paper. The proposed implementation integrates a trusted application within a secure execution environment, complemented by the inclusion of event logs to address the issue outlined in the motivating scenario. The source code is accessible at the following URL: https://github.com/dave0909/TEExProcessMining/.

To realize the implementation of trusted applications, we employed EGo,[4] a framework designed for encoding trusted application in the Go[5] programming language. Contained within the trusted application is the `Secure Miner` module, which facilitates the requisition, administration, and processing of logs from external organizations. To exemplify our approach's capability for conducting process analysis, we implemented a renowned process discovery algorithm within the `Secure Miner`.

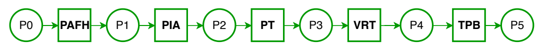
6 Discussion

In this section, we evaluate the proposed approach. The primary objective of the Sect. 6.2 is to delve into a convergence analysis by evaluating the efficacy of the collaborative data exchange process. We then took into assessment the memory usage by measuring the RAM usage in diverse parameter configurations in Sect. 6.3. In **??**, we validate the addressed approach using real-world data to conclude the discussion.

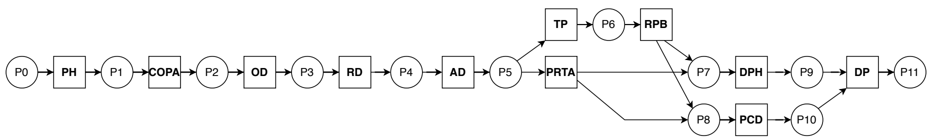
[4] https://www.edgeless.systems/products/ego/

[5] https://go.dev

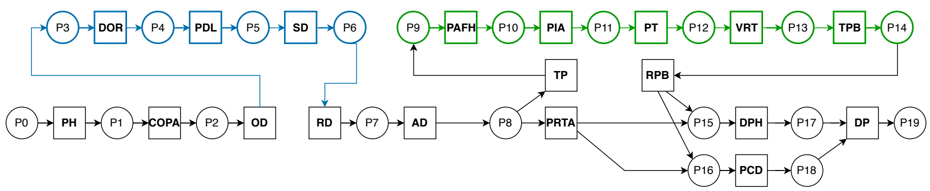
(a) Workflow net mined from the log of Pharmaceutical company.



(b) Workflow net mined from the log of Specialized clinic.



(c) Workflow net mined from the log of Hospital.



(d) Workflow net mined from the merged log in inter-organizational setting.

Fig. 7: Outputs used for the convergence test.

6.1 Datasets

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In order to generate the logs for the execution of the trusted application, we produced a simulation model based on our running example (see Sect. 3).[6] The number of log traces generated through BIMP aligns with other works in the state of the art; the generation software was set to 1000 traces. Following the generation, the synthetic event log relating to the process model was filtered via ProM.[7] We were able to filter the logs based on attribute values, which allowed us to filter the synthetic log according to the resource involved in the activities. Referring to the motivating scenario, the resources involved are the hospital, the specialized clinic, and the pharmaceutical company. In this way, we created three separate event logs from the initial event log, which were used to exchange data between the organizations.

Mention Sepsis here

6.2 Convergence

We take into analysis the convergence of the process discovery outputs, as a way of validating the correct operation of the event log exchange mechanism, . Specifically, we generated the workflow nets computed in an intra-organizational setting, in which each organization directly mines its own event log. Subsequently, we employed our approach with a miner actor that computes the same discovery

[6] https://bimp.cs.ut.ee

[7] https://promtools.org

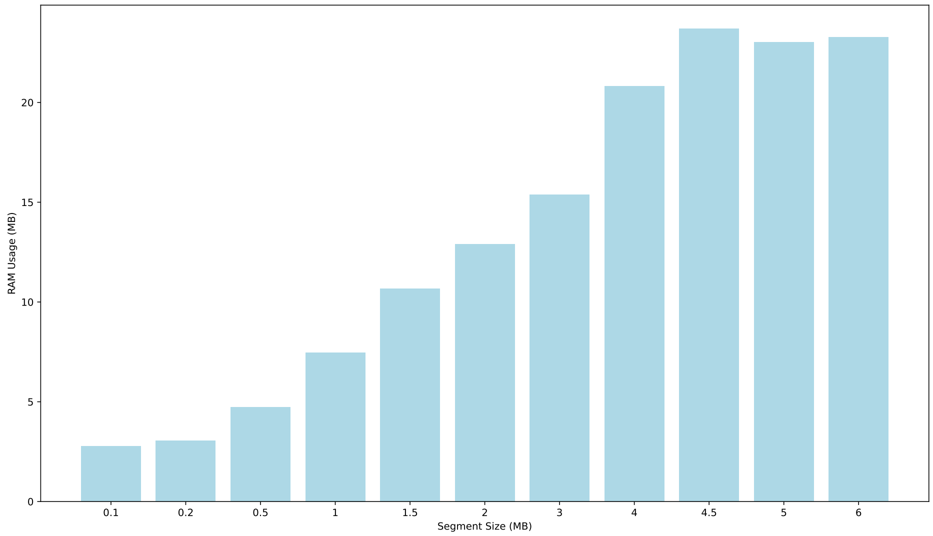

Fig. 8: RAM Memory usage for the healthcare synthetic log with 1000 traces

algorithm using an inter-organizational event log obtained as a result of the log exchange and the merging mechanisms.

To run the test, we used the synthetic event logs devised from our motivating scenario whose BPMN is depicted in Fig. 1. The size of the `Hospital`, `Specialized clinic`, and `Pharmaceutical company` event logs are 4.8 MB, 1.1 MB, and 1.6 MB respectively. Each log contains the standard value of 1000 traces, in accordance with the Sepsis Cases [11] event log.

Upon visual examination of Fig. 7, we observe that the workflow net computed through our approach, displayed in Fig. 7(d), encapsulates the structure and behavior of the workflow nets derived from the intra-organizational discovery procedures depicted in Fig. 7(a),Fig. 7(b), and Fig. 7(c). In detail, Fig. 7(a), colored in blue, depicts the process of the `pharmaceutical company` from the moment the drug order is received to its fulfillment. Figure 7(b), colored in green, depicts the process of the `Specialized clinic` from the moment the patient arrives from the `Hospital` to his transfer.

6.3 Memory Usage

grafici memory usage: segment size,

7 Conclusion and Future Work

It can be reduced

In our implementation, we have focused on process discovery tasks. However, our approach has the potential to seamlessly cover a wider array of process

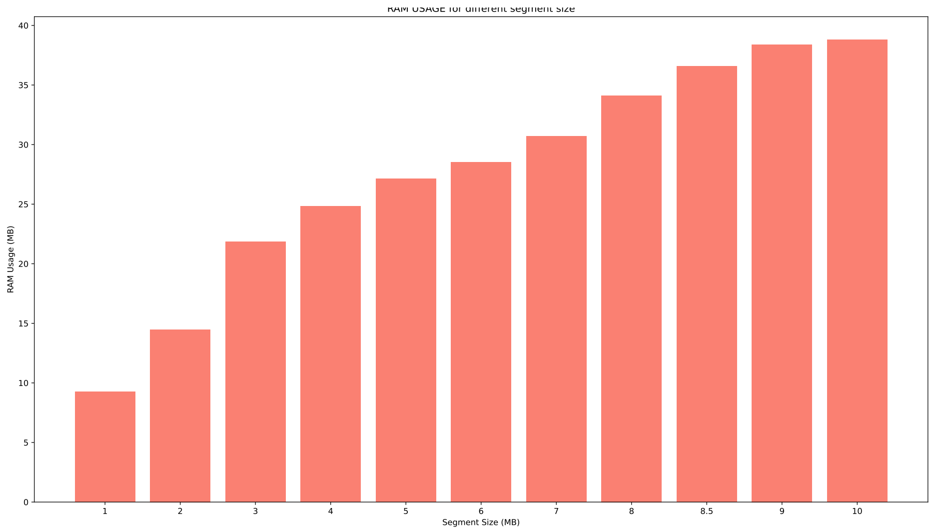

Fig. 9: RAM Memory usage for the healthcare synthetic log with 2000 traces

mining functionalities such as *conformance checking*, and *performance analysis* techniques. Implementing them and show their integrability with our approach paves the path for future work.

To be rephrased and repositioned wherever it fits best.

Confidentiality is paramount in inter-organizational process mining, as sensitive data traverses organizational boundaries. Preserving the privacy and confidentiality of operational data becomes a critical concern in this regard. Our research explores a secrecy-preserving approach in which trusted applications allow organizations to apply process mining techniques using event logs from various organizations while ensuring the preservation of partners' privacy. Our solution still has room for improvement. Currently, we assume that providers act fairly, and we do not expect to have injected or maliciously manipulated event logs. In addition, we do not handle TEE crashes and suppose that miners and providers exchange messages in perfect communication channels where no loss, no snap, and no bit corruption take place. We also make assumptions on event log data. We assume the existence of a universal clock for event timestamps across various systems, eliminating the need for synchronization procedures. Additionally, we presume that traces from different organizations relating to the same process instance share a common case identifier. However, this assumption is unrealistic in real-world scenarios, where organizations might employ different case notations. To address this challenge, we should explore alternative event log representations. Future work includes the elaboration of an interaction protocol that formalizes the communication workflow between data providers and miners. Additionally, we plan to integrate usage control policies containing terms and conditions on event log utilization. To achieve this goal, we will design dedicated mechanisms inside trusted applications for monitoring usage rules and enforcing their fulfillment.

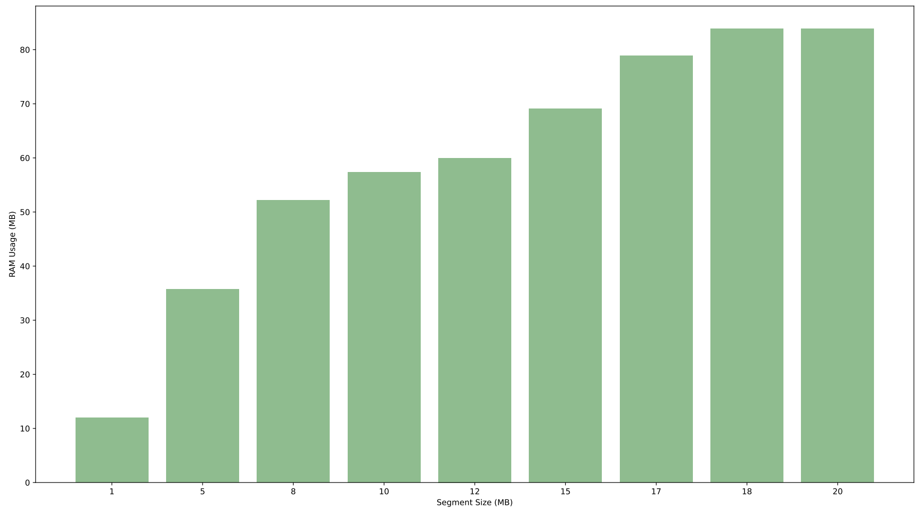

Fig. 10: RAM Memory usage for the healthcare synthetic log with 4000 traces

The presented solution embraces model process mining techniques in a general way. However, we believe that the presented approach is particularly compatible with declarative model representations. Therefore, trusted applications could compute and store the entire set of rules representing a business process, and users may interact with them via trusted queries. We plan to extend the discussion in Sect. 6 by integrating threat modeling analysis and quantitative assessments concerning scalability, throughput, and performances on real-world event logs.

CDC: The bibliography entries are too rich. Look at [7]. Do we really care that the conference was in Toulouse? And look at [10]: the acronym is enough for the conference name. Also, the volume number is useless if we do not have the series (anyway, we could not care less about either of the two). We have already gone through this, so we should shorten the entries as we know.

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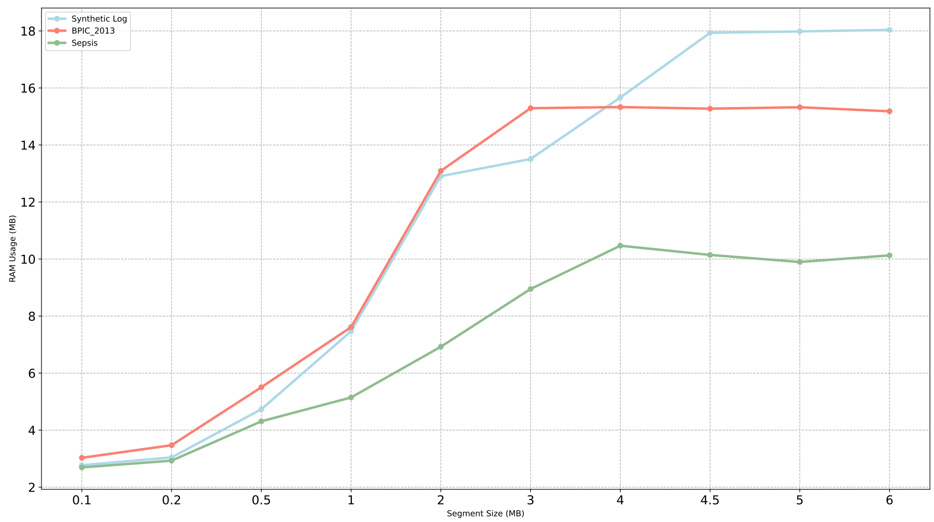

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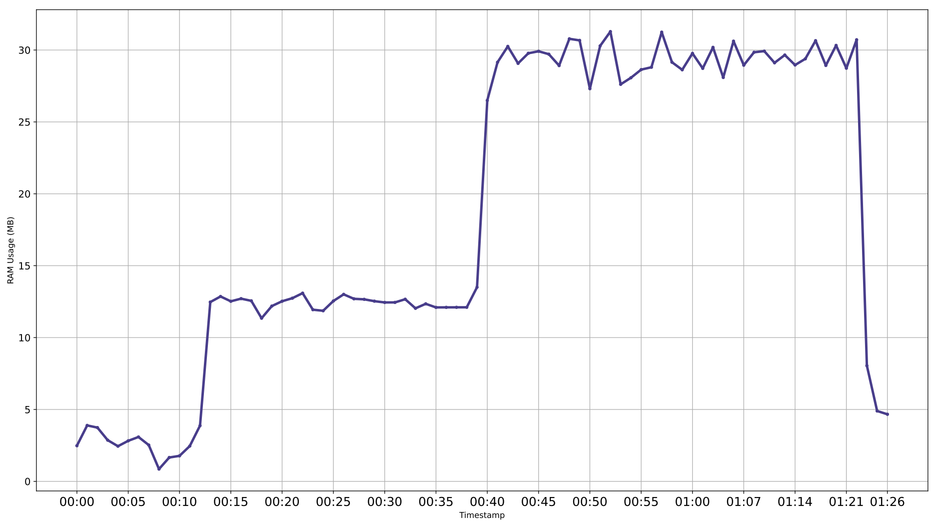

Fig. 12: RAM Memory usage for a single run for the healthcare synthetic log with 1000 traces