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EVENT LOG CONSTRUCTION FROM MULTIMODAL DATA – A REFERENCE ARCHITECTURE FOR EXPLOITING PROCESS MINING IN IT SERVICE MANAGEMENT

Short Paper

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Abstract

Process mining holds substantial potential to discover and optimize processes utilizing event log data. However, current applications primarily rely on (semi-)structured data from process-aware information systems, limiting their capacity to incorporate multimodal data from diverse sources, particularly in domains like IT service management (ITSM). While existing stand-alone approaches can extract event log data from unstructured sources such as videos, documents, or bot logs, they fall short of leveraging the full range of real-world data available in ITSM. To address this gap, our research focuses on developing a reference architecture for constructing event logs from multimodal data. This architecture integrates diverse data types, construction functions, and process mining use cases. Following a design science research methodology, we aim to evaluate the architecture through a software artifact leveraging real-world ITSM data and incorporating state-of-the-art generative AI. In this study, we present the preliminary reference architecture and share early insights from expert evaluations.

Keywords: Process Mining, Event Log Construction, Reference Architecture, ITSM, Generative AI

1 Introduction

With the ongoing digitalization, business processes are executed in information systems (IS), which produce large amounts of digital event log data reflecting the real process dynamics (van der Aalst et al., 2012). For example, IT service management (ITSM) is characterized by extensive customer interactions, which are logged throughout the service delivery process. While ITSM systems collect large amounts of data primarily for archival purposes, organizations still struggle to derive value from it (Shrestha et al., 2016). The variety of raw ITSM data—ranging from (semi)-structured tickets to

unstructured logs and notes—complicates analysis. We propose an approach to transform these data into process mining (PM)-readable event logs (van der Aalst et al., 2012). Organizations adopting PM approaches typically rely on existing (semi-)structured data tracked by IS. However, a significant portion of unstructured data is often overlooked. Kratsch et al. (2022) highlight that existing PM only considers a proportion of 10 to 20 percent of available data. Advances in artificial intelligence (AI), particularly generative AI, have made multimodal data analysis technologies accessible (Shi et al., 2019), yet research and practice still lack the clarity to fully leverage PM.

Existing approaches to transform unstructured data into (semi-)structured event logs typically focused on one type of data. For example, Kratsch et al. (2022) developed a solution for extracting event data from videos, Banziger et al. (2018) generated event log data from text data stored in customer relationship management (CRM) systems, and Egger et al. (2024) integrated bot logs and existing event log data. Unstructured digital trace data require a multimodal approach for a detailed, holistic view of business processes. Prior research also shows that event log construction goes beyond simple event recognition. To exploit the vast amounts of data, it is necessary to combine several methods to extend existing event logs in terms of identifying new activities (Banziger et al., 2018), abstracting high-level events (Baier et al., 2014), and enriching event logs with contextual data (Revina et al., 2021; Yang et al., 2014). Hence, we advocate for a multimodal approach to constructing event logs from unstructured data, addressing the following research question: *How can event logs be constructed from structured to unstructured ITSM data for use in PM applications?*

To answer the research question, we adopt a design science research (DSR) approach (Peffers et al., 2007) and develop a reference architecture for constructing event logs from multimodal data in the realm of ITSM. The reference architecture enables the systematic integration of heterogeneous data sources and tools through a structured framework for event log construction and multimodal data utilization.

2 Background

PM is defined as an approach to "*discover, monitor and improve real processes (i.e., not assumed processes) by extracting knowledge from event logs readily available in today's (information) systems […]*" (van der Aalst et al., 2012, p. 172). In PM, event logs are understood as chronological records of tracked events, including timestamps, that reflect actual processes (Cook & Wolf, 1995). An event refers to identifiable and instantaneous activities (e.g., start call, end call) (Wolf & Beverungen, 2019). The assumption is that while processes are executed, data are collected in IS or manually by human operators. An event log L contains data on process instances, also referred to as cases. Each process instance σ consists of n events $\langle e_1, e_2, ..., e_n \rangle$, describing the sequence of activities. Each event e comprises (id, a, t, c_1, ..., c_m), where id represents the unique case identifier, a the activity executed, t its timestamp, and c_1 to c_m additional context attributes. Event data can originate from various sources (Weerdt & Wynn, 2022), with core enterprise systems such as enterprise resource planning (ERP) and CRM systems being dominant. Case management and ticketing systems are also frequent source systems in ITSM PM applications. These systems keep track of when a ticket is changed in their databases. The status information is used to create an event log. Sourcing, extraction, and transformation of event data to generate an event log for PM have their challenges (Weerdt & Wynn, 2022). If the data relevant to the focus of analysis spans multiple different systems, there might not be a consistent unique case identifier. Depending on the analysis focus, a suitable case notion and event classes need to be defined (van Eck et al., 2015). The granularity levels of activities can differ significantly across source systems, requiring abstraction techniques (van Zelst et al., 2021). Activities might also not be recorded in source systems or are concealed in less structured datasets (van der Aalst, 2016). An ITSM PM application may require pre-processing steps to identify and include the activities that led to certain ticket status updates in case management systems (Baier et al., 2014).

ITSM is a compelling case for PM, as it combines technological tools like IT ticket systems with ITSM-specific human knowledge and expertise to ensure efficient problem-solving and ultimately user satisfaction. Due to these dynamic interplays and variances, understanding actual service processes spanning over scattered data sources is of great importance in managing service operations across

various service requests and incidents. However, applications of PM methods to the field of ITSM are rather scarce and consider transforming logs from IT ticket databases (e.g., ticket opening, resolution, validation, or assignment) into standard event log formats (e.g., XES) for PM methods of analysis (Baier et al., 2014). Yet, the incorporation of unstructured data, such as problem and solution descriptions, call transcripts, or additional material into a multimodal approach to PM is rarely explored.

3 Research Method

We follow the problem-centered DSR process by Peffers et al. (2007) (Figure 1), which is currently in the third phase, design and development. In the problem identification phase, we conducted a semi-structured literature review on event log construction, focusing on unstructured data and PM applications in ITSM. The findings constitute an integral part of our initial evaluation (*EVAL1*) (Sonnenberg & vom Brocke, 2012). Next, we derived design objectives (DOs) of our artifact based on the limitations of the existing literature. Afterward, we create a reference architecture for constructing event logs from diverse data. We validate the DOs and the reference architecture by interviewing six PM experts (*EVAL2*). In the demonstration phase, the reference architecture will be implemented as a software prototype using data mining and (generative) AI methods to demonstrate its feasibility (*EVAL3*). The evaluation phase tests the prototype's effectiveness and practical applicability with real-world ITSM data (*EVAL4*).

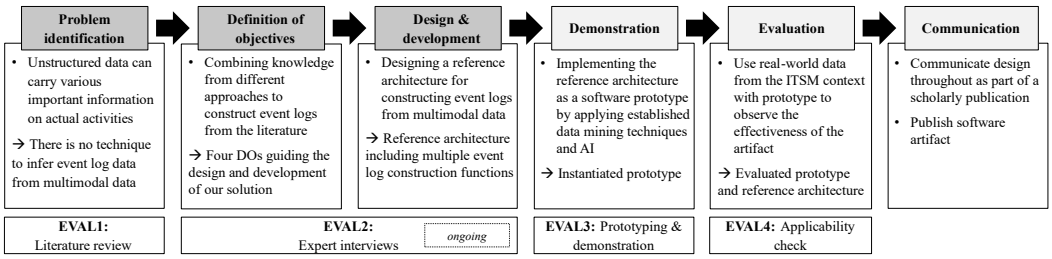

Figure 1. The first iteration of the instantiated DSR process by Peffers et al. (2007).

4 Towards Event Log Construction from Multimodal Data

4.1 Problem Identification (EVAL1)

Through a semi-structured literature review (Sonnenberg & vom Brocke, 2012), we aggregated the knowledge on event log construction and its applications to the IT service domain (Table 1). Notably, only three approaches focus specifically on event data related to ITSM (Baier et al., 2014; Elleuch et al., 2023; Gupta et al., 2020). All of these approaches use text, like descriptions in the form of work instructions, communication records, ticket comments, and emails. In terms of the focus on what should be constructed, all aim at the extraction of activities and their event log integration. When expanding the search space to other domains, it becomes apparent that other data types, construction foci, and approach functionalities exist. Data from activities executed by bots (e.g., Egger et al., 2024), or video data (e.g., Gavric et al., 2024; Kratsch et al., 2022), are used in event log construction for customer service or manufacturing processes. Only a few identified approaches focus specifically on the construction of additional (context) attributes (Yang et al., 2014). To structure the approaches' functionalities, we expanded on Diba et al. (2020), resulting in five steps: (1) parsing (including case correlation), (2) abstraction, (3) extraction, (4) integration, and (5) enrichment. Approaches outside of ITSM offer functions for parsing (e.g., Egger et al., 2024), abstraction (e.g., Banziger et al., 2018), and enrichment (e.g., Yang et al., 2014).

Our review highlights the challenge of integrating diverse data types, including video, images, and audio (e.g., screen recordings, screenshots, and customer service calls). ITSM processes also produce extensive contextual attributes (e.g., filed complaints, priority changes, or reassigned groups) that should be incorporated into event logs. Approaches need enhanced functionalities to parse logs from ticket desks, abstract activities with appropriate granularity, and enrich event logs with context data.

Paper	Domain	Data Type	Construction	Functionality
Baier et al. (2014)	ITSM	Text	Event log, activities	Extraction, integration
Gupta et al. (2020)	ITSM	Text	Event log, activities	Extraction, integration
Elleuch et al. (2023)	ITSM	Text	Event log, activities	Parsing, extraction
Kecht et al. (2021)	Customer service	Tex	Activities	Extraction
Banziger et al. (2018)	CRM	Text	Activities	Parsing, abstraction
Yang et al. (2014)	Manufacturing	Text	Event log, activities, attributes	Extraction, enrichment, integration
Egger et al. (2024)	RPA	Bot logs	Event log, activities	Parsing, extraction, integration
Kratsch et al. (2022)	Diverse	Video	Activities	Extraction
Gavric et al. (2024)	Furniture assembly	Video	Event log, activities	Extraction, abstraction, integration

Table 1. Selected, related work of event log construction.

4.2 Definition of Design Objectives

We derived four DOs for our artifact to facilitate effective PM on multimodal ITSM data and to guide the design and development of our reference architecture. The artifact should be able to process multiple types of data in an integrated way ***(DO1 – Multimodality)***. The main goal is to transform structured and unstructured data into event logs that allow applying PM methods. Thus, besides only relying on (semi-)structured data (i.e., tracked within a ticket system) (Baier et al., 2014; Egger et al., 2024), the system should support multimodality in terms of integrating multiple unstructured data sources such as text (Banziger et al., 2018; Revina et al., 2021), image (Levich et al., 2023), video (Kratsch et al., 2022), and audio. DO2 states that the artifact must provide multiple construction functions to build and extend event logs from (semi-) structured and unstructured data (***DO2 – Construction Functions)***. Constructing event log data not only relates to extracting events but is much more complex in its processing of data in terms of discovering activities, abstracting high-level events, or identifying attributes. While prior approaches emphasized the development and use of single construction functions, our artifact should connect these existing functions (i.e., *parsing*, *abstraction*, *extraction*, *integration*, *enrichment)*. Making use of the full range of event log data requires the integration of different data (***DO3 – Integration of Event Log Data)***. On the one hand, existing (semi-)structured event log data should be merged with new data (Egger et al., 2024). On the other hand, the event log construction must combine automated data processing steps as well as approaches to integrate human experts to guarantee high quality. As the motivation for constructing event logs for PM lies in generating insights from available data (***DO4 – Use Case and Data Adaptability)***, the artifact must consider multimodal data usage in two regards: (1) The pipeline should be adaptable to various use cases of PM (e.g., process discovery, predictive process monitoring, anomaly detection, etc.), and (2), it should enable users to adapt use cases to available data.

4.3 Design and Development

Guided by the four DOs, we designed a reference architecture for the semi-automated construction of event logs from multimodal data. The expert feedback from EVAL2 was integrated into the preliminary reference architecture indicated in italic formatting in Figure 2. The reference architecture consists of five main components: (1) real-world data, (2) data retrieval & preparation, (3) event log construction, (4) PM application, and (5) human-in-the-loop.

The foundation lays the ***real-world data*** component that provides access to different data sources and data types. The reference architecture should provide solutions to retrieve and understand process-related data. In the case of ITSM, this includes a) text data from problem descriptions, solution notes, scripts, emails, and communications, b) images representing screenshots, attachments, and reports, c) AI logs covering chatbot interactions, search activities, and prompts, with the potential for advanced bot and AI capabilities, and d) audio including recorded calls for troubleshooting or quality assurance. As part of this component data privacy requirements are developed, which determine particular anonymization and pseudonymization steps in the following component.

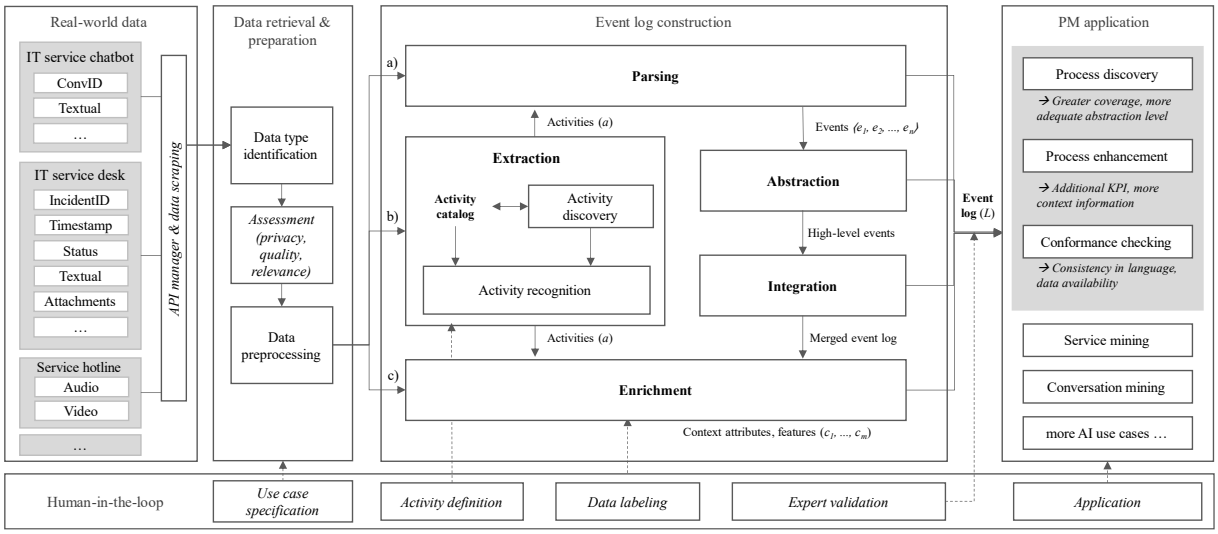

Figure 2. Reference architecture for event log construction from multimodal data.

The ***data retrieval & preparation*** component receives input data and performs three steps to transform the data into an appropriate form for the event log construction. First, data types for the available input data are identified. Second, an assessment of the data is performed, which can be realized in terms of privacy, quality, or relevance aspects. Third, data pre-processing pipelines are performed depending on the data type of the input. For example, for an event log, such a pipeline can comprise the three steps of removing duplicate data attributes, handling missing attribute values, and correcting the format of the timestamp. For processing textual data, this component can leverage natural language processing (NLP) techniques, including entity recognition and advanced preprocessing methods. When incorporating visual data, foundation models with vision capabilities, such as OpenAI's GPT-4 or Mistral's Pixtral model, are required.

At the core lies the ***event log construction*** component. It comprises all necessary functions to construct event logs at the requested granularity. We propose three exemplary paths. For example, in the case of (semi-)structured IT service tickets, an initial event log can be constructed by *parsing* status information and other (semi-)structured data into a sequence of events based on timestamps (*path a*). For unstructured textual data, such as work or solution notes, the *extraction* function identifies activities either from a predefined activity catalog or through the application of an activity discovery approach (*path b*). Based on the activity catalog, the activities are identified through a classification approach as part of activity recognition. The extracted activities are then parsed into events. In both cases, the reference architecture supports multiple levels of analysis (e.g., low-level events, high-level events, and activities) through its *abstraction* function, enabling the aggregation or decomposition of event data as needed. Furthermore, event log data from various sources, along with new and pre-existing event log data, are merged into a unified log as part of the *integration* function, facilitating integrated analysis of real-world data. Simultaneously (*path c*), or in subsequent steps, *enrichment* ensures that attributes can be derived from unstructured data using NLP and AI techniques. For example, video data can contribute knowledge on customer sentiment that enriches the existing event log. The paths are illustrative examples. Depending on the available data and targeted use case, various paths can be configured accordingly, with event logs handed over to the application component after any function.

The ***PM application*** consequently enables the creation of value in PM use cases from the constructed event logs by leveraging state-of-the-art PM tools such as the open-source python library pm4py. The reference architecture also provides recommendations for specific PM applications that align with available data while identifying potential data gaps or quality issues. Overall, the reference architecture is designed to support the three main PM types – process discovery, conformance checking, and process enhancement – while remaining adaptable to other use cases, such as predictive process monitoring (PPM).

Finally, the ***human-in-the-loop*** component reinforces that domain expertise is integrated into the construction pipeline. To ensure adaptability to various PM use cases, domain experts can specify PM applications, describe their use cases, and predefine an activity catalog, thereby streamlining the data retrieval and preparation phase. Depending on the data type, the construction functions can be triggered automatically or involve a "human-in-the-loop" approach. For example, domain experts are required to label data to predict attribute classes or validate the constructed event logs before their use in PM applications. Thereby, domain experts ensure data quality by adjusting labels and data according to the assessment within the data retrieval and preparation component. The human-in-the-loop component ensures domain knowledge integration throughout the reference architecture.

5 Preliminary Evaluation (EVAL2)

To address EVAL1, the research problem was defined through a literature review, leading to four DOs outlined in Section 4.2. To validate the developed reference architecture in terms of feasibility and clarity in an empirical setting (EVAL2), we conducted six semi-structured expert interviews. The majority of interviewees has conducted projects in the field of ITSM (Table 2). The experts were asked to identify challenges in event log construction based on their experience. Afterward, they were shown the DOs and the reference architecture and asked for their opinion, respectively.

ID	Position	Perspective on PM	PM Expertise	ITSM Exp.	Duration
I01	Chief Executive Officer	Consultant	4 years	Yes	30:23 min
I02	Business Process Consultant	Consultant	3 years	No	38:36 min
I03	Innovation Manager for PM	Consultant	10 years	Yes	30:43 min
I04	Business Process Consultant	Consultant	3 years	Yes	27:25 min
I05	Product Manager PM	PM software vendor	10 years	Yes	34:31 min
I06	Service Owner PM	User	6 years	Yes	24:43 min

Table 2. Overview of informants involved in EVAL2.

The experts confirmed the challenge of analyzing "non-standard" processes and integrating multiple data sources (I01, I02, I04, I05) in order "*to somehow integrate the[se] data into the overall process*" (I03). However, in practice, it is less about different data types and more about integrating data from various sources across multiple systems connected to business processes (I01, I02, I03), shifting the focus to accessing data via APIs and building pipelines to parse different data schemas into a unified event log. Connecting different data sources is not trivial as I04 states: "*It's not always just about two datasets… Instead, the relationships or rules were often much more complex. This was also the case with the ITSM cases we worked on, where data didn't come in a format that made it easy … you really had to invest time and effort into figuring out what the changes you were looking for actually were*." I03 and I06 stress that data privacy remains a bottleneck, and therefore the reference architecture should incorporate filters, not only for data privacy but also for data quality and relevance. Furthermore, the experts emphasized that the underlying process of constructing event logs is not one-way and requires multiple iterations (I04). As such, I04 assumes "*that the different datasets must first be analyzed separately and then eventually merged at a later stage*". The experts propose two main approaches to transforming data into business value. First, the reference architecture should support a data-driven approach, enabling the identification of potential use cases based on underlying data (I04). Second, it should facilitate a use case-driven approach by determining specific data needed for a given use case or a predefined goal (I01, I02). Regarding the construction functions, the interviewees emphasized extracting activities and abstracting high-level events as the most interesting functions while parsing refers to a default approach in practice: "*With this activity catalog and the abstraction aspect, it's also about extracting what is truly relevant*" (I02). Experts generally agree that state-of-the-art NLP technologies, including large language models, are well-suited to enhancing event log construction (I01, I03). However, human-in-the-loop configurations remain essential for ensuring the quality of event log data by incorporating rules, feedback, and validation (I01, I03). In summary, PM experts conclude that the reference architecture is valuable for increasing process transparency, identifying automation potential, and targeting the most appropriate level of abstraction (I03).

6 Discussion and Plan for Future Research

Our study provides a preliminary reference architecture for constructing event log data from multimodal data. We aggregated prior knowledge on event log extraction and integration (e.g., Egger et al., 2024; Kratsch et al., 2022) and identified a gap in the literature for a broader view of event log construction for PM use cases in ITSM. As part of our DSR approach, PM experts from the industry were involved in evaluating the artifact. They agreed on the main components of the reference architecture, especially concerning the construction functions parsing, abstraction, extraction, integration, and enrichment. Through the evaluation, we added an assessment step in data retrieval to address privacy, verify quality, and filter relevant data—while our iterative design emphasizes domain knowledge via a human-in-the-loop component. The reference architecture contributes to the existing body of knowledge in PM for event log construction (e.g., Baier et al., 2014; Kecht et al., 2021) by introducing a novel and general model developed through the application of DSR. Our study broadens the scope of event data to be used in PM for ITSM by including parsing, abstraction, and enrichment next to event extraction and integration (e.g., Elleuch et al., 2023; Gupta et al., 2020). The addition of further process context enables an expansion of PM applications towards a more holistic view of real-life processes (van der Aalst et al., 2012). For practice, the reference architecture can represent the missing link to making vast amounts of available data usable for various PM applications in ITSM. Industry PM experts saw the reference architecture as a useful guide for event log construction in their use cases.

We aim to continue our preliminary evaluation (*EVAL2*) by approaching additional practitioners with expertise in PM. Subsequently, we plan to instantiate the reference architecture in the form of a software artifact. We aim to address potential limitations related to data privacy and data quality that may arise from applying our architecture. This requires mechanisms to ensure data privacy and validate the quality of the underlying data. To further enhance our approach, we plan to expand our research on the human-in-the-loop component, exploring synergies between humans and AI in sensitive areas in the ITSM domain. We intend to use the feedback from the conference Win upcoming iteration cycles, aiming to enhance the artifact and implement it within an ITSM organizational context. The addition of an object-centric perspective within the reference architecture by constructing an object-centric event log might be a relevant consideration (van der Aalst, 2019). Especially in the ITSM domain, for example, differentiating between views on customers and incidents can offer a detailed analysis of how customers interact with IT services in an organization. The proposed architecture can further be generalized to be applied in other domains, such as healthcare or manufacturing.

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